MAPPING THE TWITTER LINKAGES BETWEEN AMERICAN POLITICIANS AND HATE GROUPS

A thesis submitted in partial fulfilment of the requirements for the Degree of Master of Science in Mathematics and Statistics in the University Of Canterbury by

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Abstract

Big Data is a growing field after social media allowed developers to collect and store data using various platforms. The present research utilises Twitter data and Apache Spark to extend and develop an easy to implement method to test a contemporary question of interest. Specifically, I focus on Donald Trump's campaign for the President of the USA. Donald Trump's campaign had been very controversial from the start, following his hostile views expressed toward immigrants and minorities. During this time, media pundits and the public spent much time debating whether Trump's campaign was motivated by hate or other factors. The present work examines whether Donald Trump had unique appeal to hate groups by examining the twitter linkages between several American political leaders (Donald Trump, Hillary Clinton, Bernie Sanders, Ted Cruz, and Paul Ryan) with American hate groups. The results show that users who often retweet Donald Trump are more likely to frequently retweet American hate groups such as Neo Nazis, White Nationalists, anti-immigrant, anti-Muslim, anti-LGBT, and anti-government groups, more than any other politician. While other Republican politicians were also linked to anti-immigrant, anti-Muslim, and anti-LGBT groups, it was to a lesser extent than Trump. This data suggests Trump may have had unique appeal to American hate groups.

Mapping the Twitter Linkages between American Politicians and Hate Groups

Twitter is a micro-blogging service that has emerged as a popular and effective way of peer-to-peer communication (Jansen, Zhang, Sobel, & Chowdury, 2009), especially after its role in the Arab Spring and successful recruitment campaigns by extremist groups (Hermida, Lewis, & Zamith, 2014). On Twitter, users can express what they think and feel in real time. They can express their opinions on various social and political issues; they can comment about media programming or celebrities; and they can even evaluate and advertise consumer products. Social media gained influence during the 2008 US Presidential election of Barack Obama, whose campaign provided new opportunities for online social media applications, including microblogging services during the campaign (Smith, 2009). Since then, a number of political leaders use Twitter to reach their followers by tweeting their agenda during elections (Adams & McCorkindale, 2013; Choy, Cheong, Laik, & Shung, 2011) and Twitter has even been used to predict election results (Tumasjan, Sprenger, Sandner, & Welpe, 2010).

The Challenges of Analysing Big Data (Twitter)

A tweet is a text message that is no more than 140 characters in length. On average, there are about 6000 tweets per second on Twitter, which is around 500 million tweets per day and 200 billion tweets per year (Internet Live Stats, n.a.). This makes Twitter one of the largest social networks in the world (Internet Live Stats, n.a.), allowing social scientists to examine the properties of social groups and networks. Nevertheless, even though Twitter is a very popular social interaction platform, some users could employ other platforms for communication, including Facebook, Reddit, 4chan. While previous research has largely relied on self-report surveys to understand individual interactions and social networks in the larger population (Gentzkow & Shapiro, 2011; Pfau, Houston, & Semmler, 2007), such approaches are subject to social-desirability bias and/or measurement error. In light of these limitations, recent work has begun to explore social attitudes and behaviour on platforms like Twitter (Bakshy, Messing, & Adamic, 2015; Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). The present research similarly observes social interaction and influence within a large social environment to investigate a social / political question of contemporary interest, for example, the reaction of Twitter users to President Trump’s unique approach to politics. However, this research acknowledges that the interactions on social media do not represent those of all society. While social media provide people with the means to voice their opinions freely and publicly (Chadwich, 2008; Hilbert, 2009), not all people use social media.

Donald Trump and the USA 2016 Presidential Election

Donald Trump is a businessman and television personality who announced his candidacy for President of the USA on 16th June 2016, using the slogan “Make America Great Again” (*Time*, 2015). Trump was one of the most controversial presidential candidates in American history because of his lack of political background and openly negative views of various groups including Muslims (Revesz, 2016), women (Cohen, 2017; *Time*, 2015) and Mexicans (Berg, 2015). Even though some research claims that having a leader with hateful ideas results in the party general-election vote share decreasing by approximately 9–13% on average (Hall, 2015), Trump was able to increase the party vote and win the 2016 American Presidential Election (Le Miere, 2016).

During the election, two narratives emerged in the media to explain Trump’s rise to power. The first narrative argued that exasperation with the current political structure (Margolis, 2016; Scott, 2015) and the increase of unemployment and poverty in the US over the last 30 years gave rise to genuine uncertainty and angst (Amy, 2011; Muro, 2016). Trump’s rise under these conditions could be explained by the uncertainty-identity theory

(Hogg, 2007), the need for closure (Kruglanski, Pierro, Mannetti, & De Grada, 2006; Van Hiel, Pandelaere, & Duriez, 2004), or motivated social cognition (Jost, Glaser, Kruglanski, & Sulloway, 2003; Kruglanski, 1996) which generally suggest that feelings of uncertainty and angst can result in the formation of inflexible, nationalistic, and extreme political beliefs, such as right-wing authoritarianism (Altemeyer, 1998). The second narrative argued that Trump's rise was motivated by increased feelings of identity threat, dividing Americans into 'us' versus 'them', and alienating minorities. This could be explained by relative deprivation theory (Runciman, 1966; Walker & Pettigrew, 1984), intergroup threat theory (Stephan & Stephan, 2000), perceived threats to group social identity and status resulting from increasing ethnic diversity (Craig & Richeson, 2014; Major, Blodorn, & Major Blascovich, 2016). While both narratives could have played a role in Trump's rise to power, the latter explanation is one that is still heavily debated, raising the need for empirical work to examine whether Trump had unique appeal to hate filled individuals or groups. Some argue that Trump's rhetoric could have changed the norms of American society, making it acceptable to be a bigot (Flitter & Kahn, 2016; Frank, 2016; The Texas Politics Project, 2016). As a result of this hate groups like Ku Klux Klan (KKK) and Neo-Nazi groups openly supported Donald Trump's candidacy (Holley, 2016; Neiwert & Posner, 2016).

In the present research, we examine whether Trump possessed unique appeal for hate groups during the election. As Twitter has become a preferred social media platform for political leaders, including Trump, who continues to use it after being elected as the President of the USA (Fahey, 2017; Times, 2017), we chose to focus on Twitter networks of American political leaders. We compared Trump's Twitter network to that of four other American political leaders, including: Hillary Clinton, Bernie Sanders, Ted Cruz, and Paul Ryan. Clinton was chosen as she was the presidential rival of Trump. Sanders and Cruz were chosen as they were the runner-up Democratic and Republican candidates during the election. And

Ryan was chosen because he is the Speaker of the House and considered a traditional Republican providing. This diversities of these politicians' affiliations were the base for this research comparison.

Hate Groups in the USA

In this research, we used the Southern Poverty Law Center (SPLC)'s website to collect data on American hate groups (Southern Poverty Law Center [SPLC], n.d.-b). SPLC aims to fight hate and to seek justice for vulnerable people by using education and litigation ([SPLC], n.d.-b). The SPLC database which classify hate groups and their leadership in the USA is one of the most comprehensive in the last 40 years (Freilich & Alex Pridemore, 2006; Jonsson, 2011). Even though SPLC has been the centre of controversy (Curtis M. Wong, 2015; Nawaz, 2016), it is still the best available US database for individuals and groups made available to the pubic (Freilich & Alex Pridemore, 2006). Not all the groups and individuals on the SPLC list have been included because they are violent, but because their views and ideas alienate an entire class of people. The SPLC database has only American hate groups that espouse several major ideologies including Anti Government, Anti-Immigrant, Anti-LGBT, Anti Muslim, Christian identity, Ku Klux Klan, Neo-Nazi, Neo Confederate, Racist Skinhead, and White Nationalist ([SPLC] ,n.d.-a). The complete list is in Appendix A.

The Present Study

This thesis will focus on obtaining Twitter data and analysing it using models and inference methods in order to statistically test a contemporary political question of interest. Given Twitter's popularity and status (Honey & Herring, 2009), tweets could be considered as "electronic word-of-mouth" (Jansen et al., 2009), but with an ephemeral timespan (Christensen & Christensen, 2008). In this research retweets were used to measure users' interactions. Retweeting is a way of ratifying someone's tweets by broadcasting the content to the retweeters' followers (Conover et al., 2011)

Apache Spark (Apache Software, n.d.), and Twitter API (Twitter Inc, 2017) were used to construct a programmatic solution that could be used not only for Twitter but also for other social media platforms to explore the under-utilized, millions of nodes, large-scale data sets, especially in observable social networks. Two methods of data collection were used to convey information about individual users' political interaction: first using Twitter Streaming API (Twitter Inc, 2017) to collect data for one set of Twitter IDs including SPLC's hate groups ([SPLC], n.d.-b) ([SPLC] ,n.d.-a) and major politicians including Trump, Clinton, Ryan, Sanders, and Cruz. The second data collection method used Twitter Rest API to collect users' timelines (last 200 user interactions including tweets, retweets and mentions) for users who tweeted Trump and Clinton on the last presidential debate to ensure the inclusion of a sample of the politically engaged from both parties. A random sample of a third of all users' tweets were collected, which included all verified and geo-enabled accounts, to try to eliminate bots as much as possible (Boshmaf, Muslukhov, Beznosov, & Ripeanu, 2011; Dickerson, Kagan, & Subrahmanian, 2014; Wald, Khoshgoftaar, Napolitano, & Sumner, 2013). The combination of the data from the two methods allowed this research to launch a model that preserves the innate differences among users' tweet and retweet rates, to regulate the size of the twitter networks and the number of tweets by a specific individual. Text-processing was not used in this research to eliminate the methodological limitations associated with content analysis (Kouloumpis, Wilson, & Moore, 2011; Saif, He, & Alani, 2012).

The aim of this research was to provide a quick, easy-to-reproduce method with minimum manual data collection to investigate a social / political issue. In this case, the research tries to answer an issue, hotly contested in the media of whether Trump possessed unique appeal for American hate groups. The first hypothesis was that users who retweet the SPLC hate groups would retweet Donald Trump more than any of the four other candidates. The second hypothesis was that the type of hate group ideology would play a role in the percentage of users who retweet a specific group and any one of the five politicians. For example, we would examine whether Alt-Right, Anti-Government, Anti-Immigrant, Anti-Muslim, Ku Klux Klan, Neo-Nazi, Neo Confederate, and White Nationalists are more likely to retweet Trump than any other politician because of Trump's strong narrative against immigrants, minorities, and the existing political system. Therefore, Trump may have had unique appeal to members of these groups'. However, there is unlikely to be any difference in the amount of retweeting of Anti-LGBT, Christian identity, and Black Separatist groups between Trump and the other American political leaders as his campaign was not largely focused on promoting these ideologies.

Method

Twitter Network

A Twitter user can have millions of followers; each follower receives a status update when the user posts an update. A Twitter user does not require permission to follow another (Conover et al., 2011). There are two main public ways for Twitter users to interact with each other: retweets and mentions (Boyd, Golder, & Lotan, 2010; Conover et al., 2011). This research used only retweets as they are considered to be a strong index of not only interest in the message, but also confirmation and confidence in the communicator (Boyd et al., 2010; Metaxas et al., 2015). Retweets are an efficient way to pass news and attention-grabbing discoveries on Twitter (Boyd et al., 2010; Metaxas et al., 2015). Retweets do not involve further natural language processing significantly simplifying the analysis compared to quoted tweets, where the user re-post' a tweet with a text to agree or disagree with the original tweet. Twitter users can retweet their own tweets as well as those of someone else, allowing users to be engaged without directly addressing the original twitter (Marlow, 2005).

Twitter Data collection

The present analysis was powered by data collected using two different methods: first, the Twitter streaming API collection method to gather tweets for nearly nine weeks, four before the presidential election and four after; second, the Twitter Rest API collection method which accumulated the 200 most recent interactions (tweets, retweets, mentions) for a random sample of about a third of all users, who retweeted Trump and Clinton on the 3rd presidential debate. The data establishes an evenly represented sample of politically active Twitter users from the two parties. The Rest API Job added 0.3 million users to the retweet network and increased the number of retweets from 10.5 million to 13.7 million.

Twitter streaming API collection

The Streaming API method collected all users' interactions, including tweeting, retweeting, and mentions for the American political leaders and 52 Twitter accounts from SPLC's database of hate groups and hate group leaders. Although we aimed to have the Streaming collection running nonstop for the specified period of time, there were short breaks in the data collection for uncontrolled external reasons such as the cluster crashing. The process was restarted immediately after discovering the crash. The Scala program is in Appendix B.

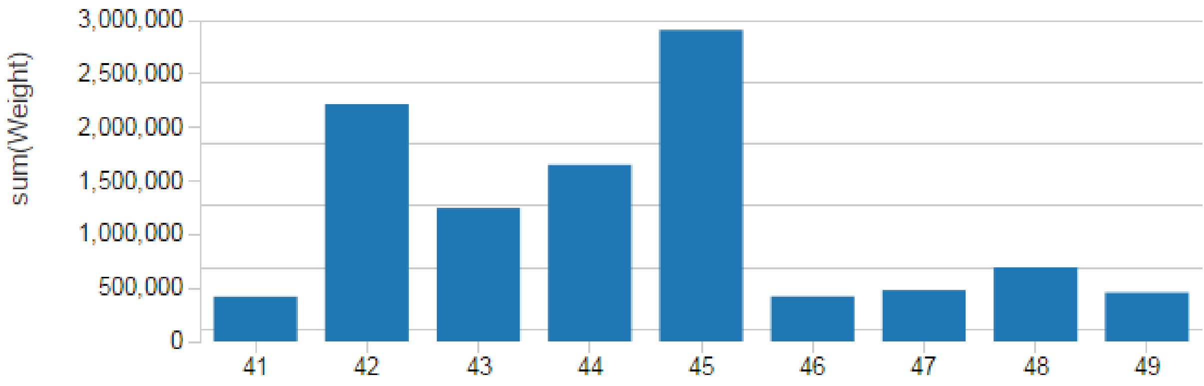

Figure 1. The sum total of number of tweets per week

Figure 1 shows the number of retweets per week of the year. There are more retweets in week 42 due to the third US Presidential debate between Clinton and Trump followed by a spike in week 45 (election week). Technical interruptions explain the reduction of tweets; given that these interruptions happened on uneventful days, there was confidence that the sample captured the communications of interest to the study. A total of 7 million of the 10.5 million retweets occurred on the same day as the original tweet, and 98% of the retweets happened within a week of the original tweet, which indicated immediate reactions to interesting information or ideas.

Twitter Rest API user timeline collection

The Twitter Rest API method collected the 200 most recent status updates, for example, tweets, retweets or mentions. It targeted a random sample of a third of all users who retweeted either Clinton or Trump on October 19, 2016 (last Presidential debate), to produce directed edges to our retweet network. Breath-First expansion was used to combine the set of users in the Twitter timeline and the retweet network to expand the 9-week-long Retweet Network. The program used to collect the user time line is Appendix C.

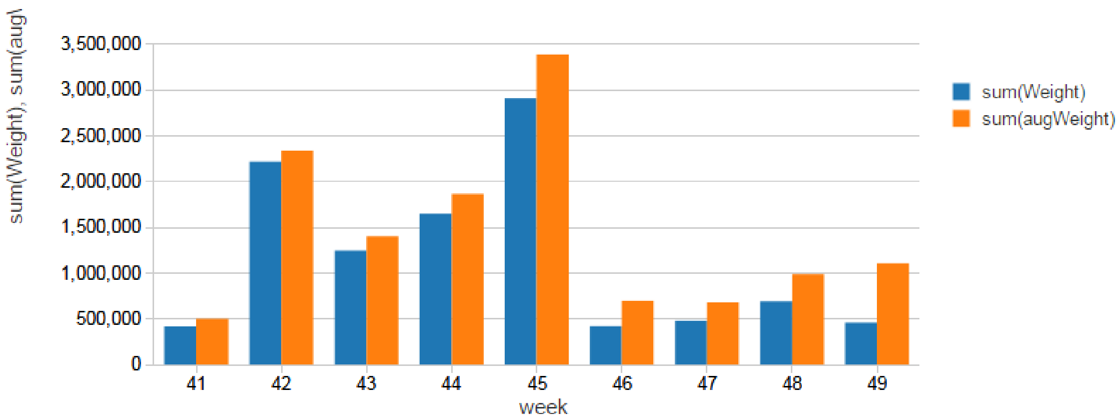

Figure 2. The number of retweets per week and per day of the year with and without such an augmentation.

Crucially, Figure 2 shows that this augmented data added another 0.3 million users to our network and increased the number of retweet events from 10.5 million to 13 million.

Identifying Hate Groups

The SPLC website was used to identify primary hate groups in the USA (Appendix A). A manual search was used to identify and locate some of the twitter accounts for the users or groups stated on the SPLC website. Only 77.61% of the identified hate groups and leaders had an active twitter account. That limited our study to only SPLC hate groups with active public Twitter accounts. Nevertheless, it is a good representation of public interaction and hate groups. Thirty Twitter accounts were found for the SPLC hate groups, and another 22

Twitter accounts were established for the SPLC hate group leaders. Only the 52 Twitter accounts belonging to 13 hate groups identified by SPLC were included as a filter in the streaming job to collect all their Twitter interactions or any interaction that included them while the streaming method was running. Figure 4 demonstrates the number of followers on Twitter for each of the hate groups.

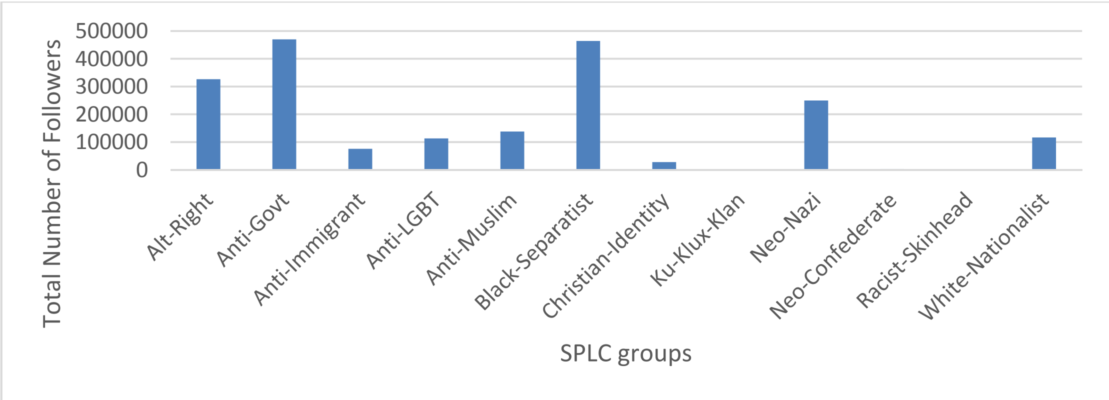

Figure 4. Number of followers per SPLC groups

Political key players

Key political twitter accounts were used to identify political communication as all Twitter users' interactions (mentions, tweets, retweets). The politicians whose interactions the streaming process collected for were Sanders, Ryan, Trump, Clinton and Cruz.

Permute and Crosswire algorithm

This research used the Permute and Crosswire algorithm (Zaharia, 2016) which was implemented in Apache Spark, the fastest available engine, because of its scalability for large networks. First, Permute was used as a way of ordering and rearranging a set of elements. This research combines all retweets from both Streaming API and Rest API, in to a total number to identify users who retweeted the politicians' or any of the hate groups or their leaders'[1] twitter accounts which resulted in direct edges of the retweet network, *G*; a uniform variable, *u* (the number of users' retweets), was associated with each edge in *G*; then the edges in G were sorted according to their associated *u*'s. Second, adjacent pairs of edges in the permuted G were cross-wired. This research cross-wired the users who retweeted any of the politicians with users who retweeted any of the hate groups to develop a network for each pair of the adjacent edges *e_1 = (a,b)* and *e_2 =(c,d)* and cross-wired them into *e_1=(a,d)* and *e_2=(c,b)*. The total number of retweeters were thereby combined for all the target Twitter lists which included the politicians' and the hate groups' accounts, then cross-wired to have the politicians versus the hate groups or their leaders to develop a combined number of users who retweeted both the politicians' and the hate groups' accounts.

After permuting the edges and cross-wiring the number of times each user retweets others and is retweeted by others, the number of times remains the same as that of the observed network. To preserve the observed in and out degrees, independent samples of the retweets network had the algorithm applied, then it was transformed into a statistical test to obtain the sample null distribution. If 99.9% of the sampled test statistic had been less extreme than the observed test statistic, then the null hypothesis would be rejected with a *p*-value of 0.01. However, this model frees up information on who exactly retweets whom, providing the out-degree and in-degree of each user, i.e., the number of times each user is retweeted by others and is retweeted. The observed network is the same as the original network.

[1] Not much activity was recorded for Ku-Klux-Klan, Neo-Confederate and Christian Identity groups, which made it impossible to develop a conclusion about their interactions. It may be that the groups identified by SPLC under these ideologies use private social media platforms such as 4chan or reddit instead.

Null model for retweets

An "apathetic" model is implemented by choosing a user at random from all users, while preserving each observed rate of tweeting and retweeting. This is called the directed, multi-edged, self-looped configuration model in random graph theory (Aldous, 2013). A simple randomised algorithm is devised to produce samples from this null model. The null distribution of any network statistical test can be directly obtained by applying it to each of the randomised algorithms. The number of Twitter users who retweeted a politician and hate groups or their leaders at least five times each was obtained, along with their 99% confidence intervals under the null apathetic retweeting model. The number of five retweets was used to represent at least one retweet per fortnight over the 9 week period of observation.

Results

To eliminate the impact of the large number of Trump's tweets, compared to the tweets of any of the other four politicians, a sampled retweet network from the null configuration model is used to obtain the null distribution of various statistical tests. Thus the observed differences in the tweets and retweets were preserved between the in-degree and out-degree of every network user (Appendix D).

Table 1

The observed relative frequency of retweets by any one of the hate groups or their leaders for each of the five candidates

Dataset	F[DT]	F[HC]	F[BS]	F[TC]	F[PR]
Percentile Confidence Interval	99%*	0%	0%	1%	0%
Lower Confidence Interval	0.60	0.26	0.07	0.00	0.00
Upper Confidence Interval	0.65	0.30	0.09	0.01	0.01

Note. *$p < 0.001$

This means that 99% of the users who retweeted any of the hate groups also retweeted Trump (DT) which is higher than any of the other two Republicans, Cruz (TC) and Ryan (PR), or the two Democrats: Clinton (HC) and Sanders (BS).

These results showed that none of the five political leaders retweeted any of the 194,098 hate groups' original tweets. On the other hand, 151 of Trump's and 2 of Cruz's original tweets' were retweeted by one of the hate groups' leaders out of 7,233 retweets, retweeted by the hate groups. The hate groups or their leaders who retweeted the 151 Trump retweets were: Neo-Nazi (87), White-Nationalist (55), Anti-Muslim (6) and Anti-Government (3). Neo-Nazi and White-Nationalist group leaders were the two who retweeted Cruz.

Table 2

The in-degree, out-degree results of any one of the hate leaders' retweeters for each of the five candidates

Politician	**In-degree**	**In-Nbhd**	**Out-degree**	**Out-Nbhd**
Trump	40	12	5,952,257	958,262\\
Clinton	225	121	2,774,111	943,995
Sanders	107	62	762,209	356,718
Ryan	769	158	68,973	28,902
Cruz	322	189	49,479	27,663

In-degree: Number of retweets by the politician
In-Nbhd: Number of retweets by the politician for unique users
Out-degree: Number of time the politician is been retweeted
Out-Nbhd Number of times the politician is been retweeted by unique users

Despite Trump being retweeted more than twice as often as Clinton (Out-degree), the numbers of unique users who retweeted Trump and Clinton were almost identical (i.e., Out-Nbhd). This could be interpreted to mean that Trump was retweeted more than Clinton because he tweets more than Clinton and that Trump was being retweeted randomly without any preference for him over the other politicians. To control for this effect, the Permute and Cross-wire algorithm was used to obtain samples from the joint distribution of the relative frequencies under the null hypothesis of apathetic retweeting. The observed statistic lies outside the 99.9% confidence set obtained from 1000 samples from the null. The initial results showed that Donald Trump had a statistically significantly higher rate of users from all the hate groups' accounts retweeting him.

The following graphs represent the statistical results. When the observed counts fall within the confidence intervals, then we cannot reject the null. However, if the observed count is outside the confidence interval, and specifically higher, then it would suggest a statistically significant effect. There were no multiple testing issues or problems associated with independence assumptions because of the joint distribution of the counts under the null model that preserves the observed in and out degrees in the observed retweet network. See Appendix D for the complete results.

Anti-Government groups

Anti-Government groups had the most followers in the data set. Figure 5 demonstrates that the number of anti-government users who retweet Trump is significant, and in fact, the only statistically significant number compared to the other four candidates.

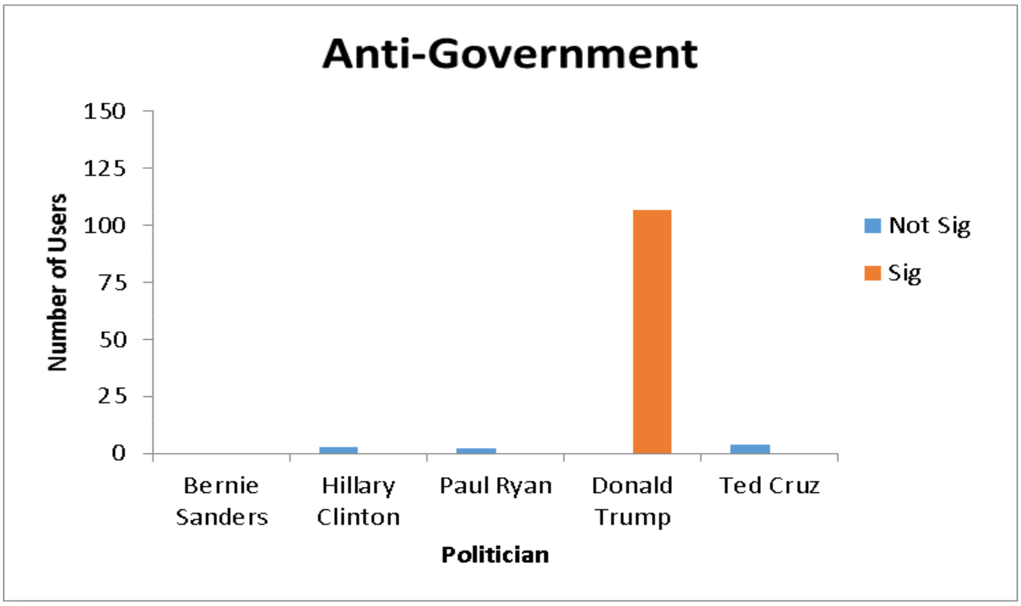

Figure 5. The number of users who retweeted the Anti-Government groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

Anti-Immigrant groups

Figure 6 shows that Ryan, Trump and Cruz were all significantly associated with Anti-Immigrant users, but the number of users who retweeted Trump is substantially higher than those retweeting Ryan and Cruz.

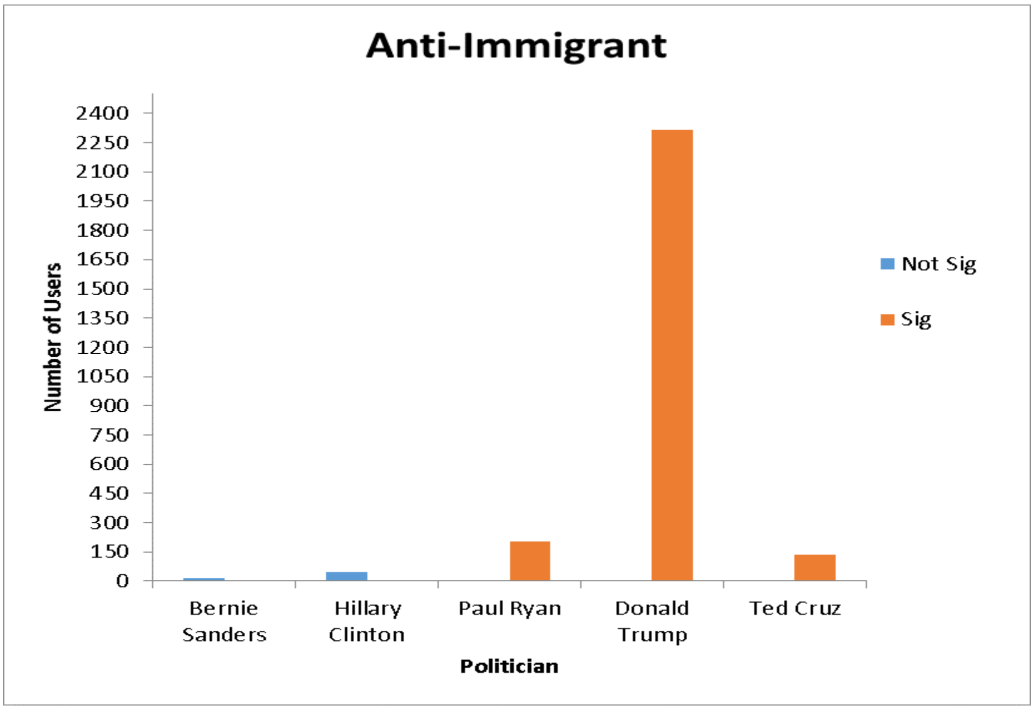

Figure 6. The number of users who retweeted the Anti-Immigrant groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

Anti-LGBT

Figure 7 shows that Ryan, Trump and Cruz were all significantly associated with Anti-LGBT groups, but the number of users who retweeted Trump is considerably higher than those retweeting Ryan and Cruz.

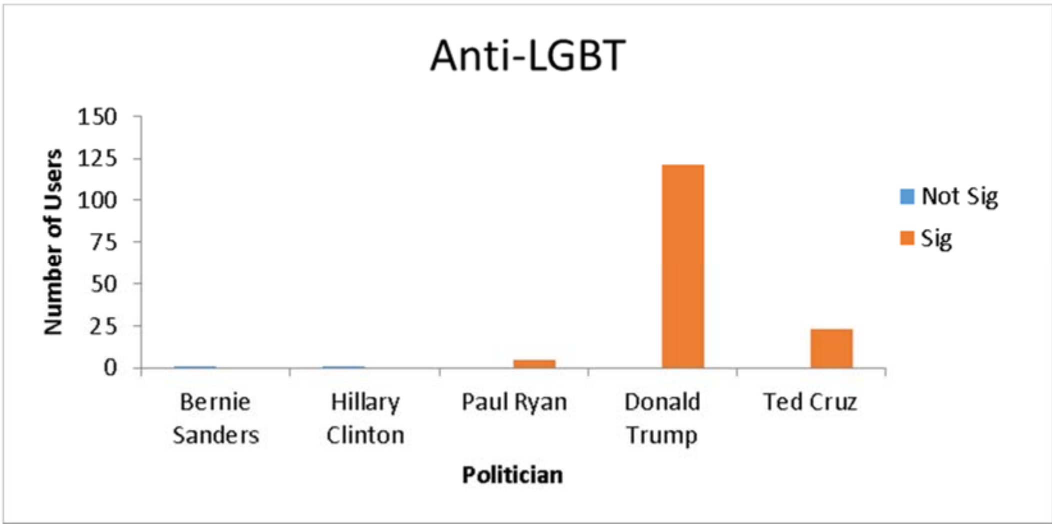

Figure 7. The number of users who retweeted the Anti-LGBT groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

Anti-Muslim

Figure 8 shows that Ryan, Trump and Cruz were all significantly associated with Anti-Muslim groups, but the number of users who retweeted Trump is considerably higher than those retweeting Ryan and Cruz.

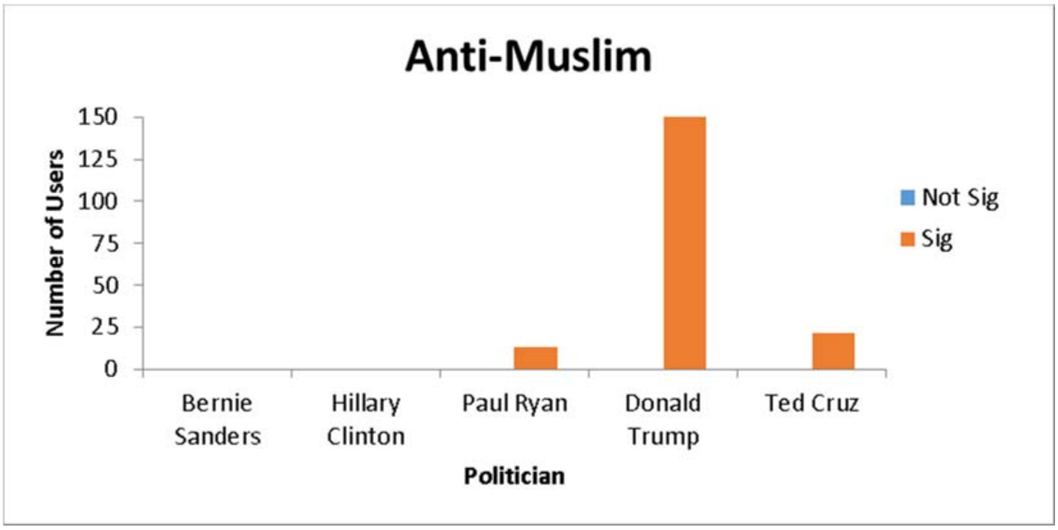

Figure 8. The number of users who retweeted the Anti-Muslim groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

Neo-Nazi

Figure 9 demonstrates that a significant number of users who retweet Neo-Nazi groups also retweet Trump. In fact, Trump is the only politician in the data with statistically significant linkages to this ideology.

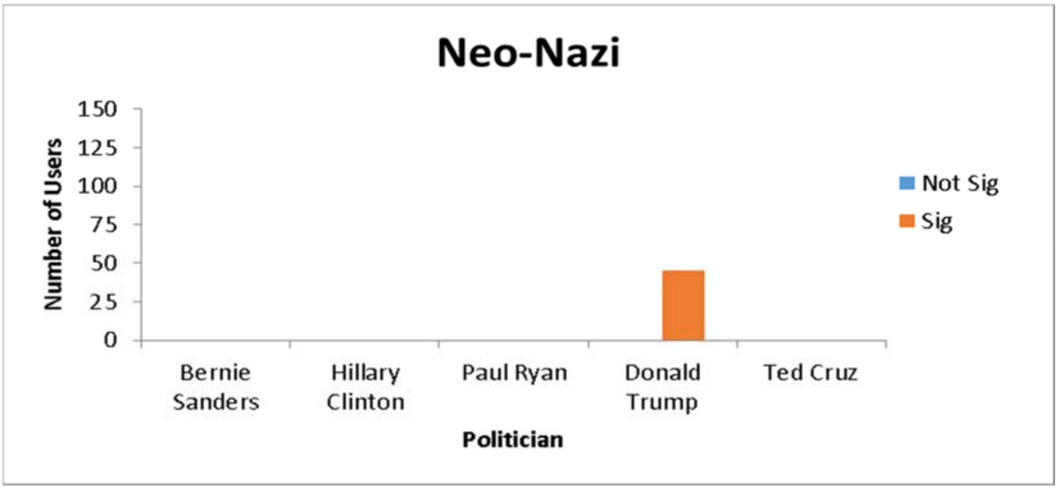

Figure 9. The number of users who retweeted the Neo-Nazi groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

White-Nationalist

Figure 10 demonstrates that a significant number of users who retweet White-Nationalist groups also retweet Trump. In fact, Trump is the only politician in the data with statistically significant linkages to this ideology.

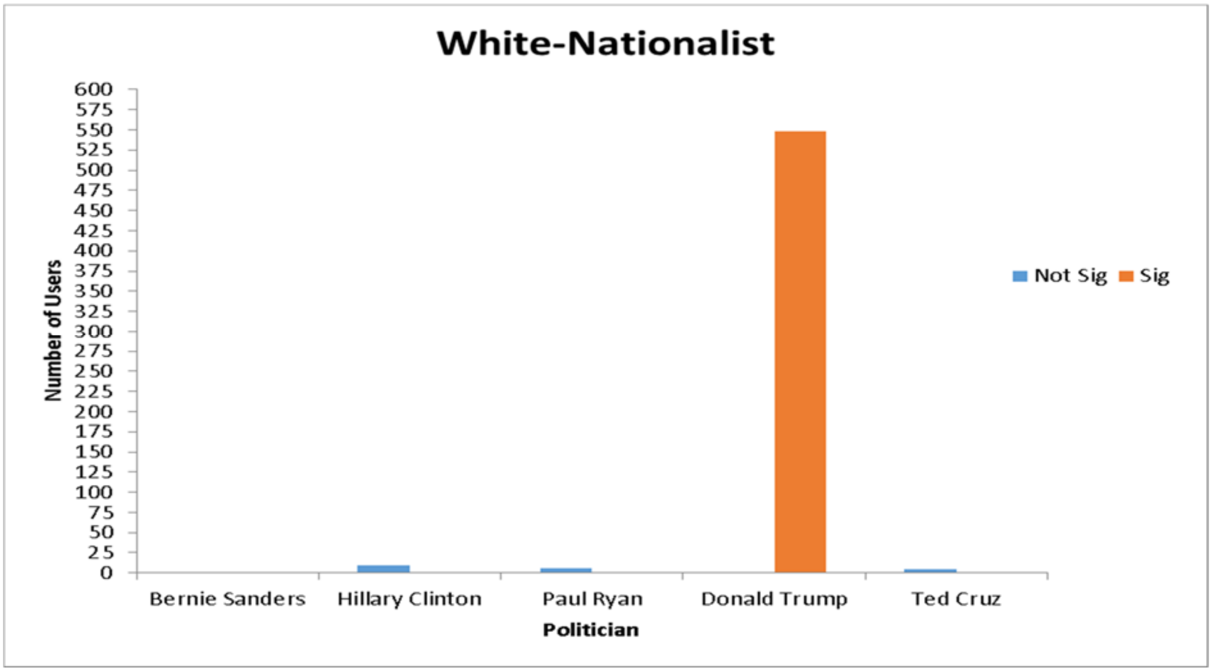

Figure 10. The number of users who retweeted the White-Nationalist groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

Black-Separatist

Figure 11 demonstrates that retweeters of Black-Separatist groups did not significantly retweet any of the five political leaders.

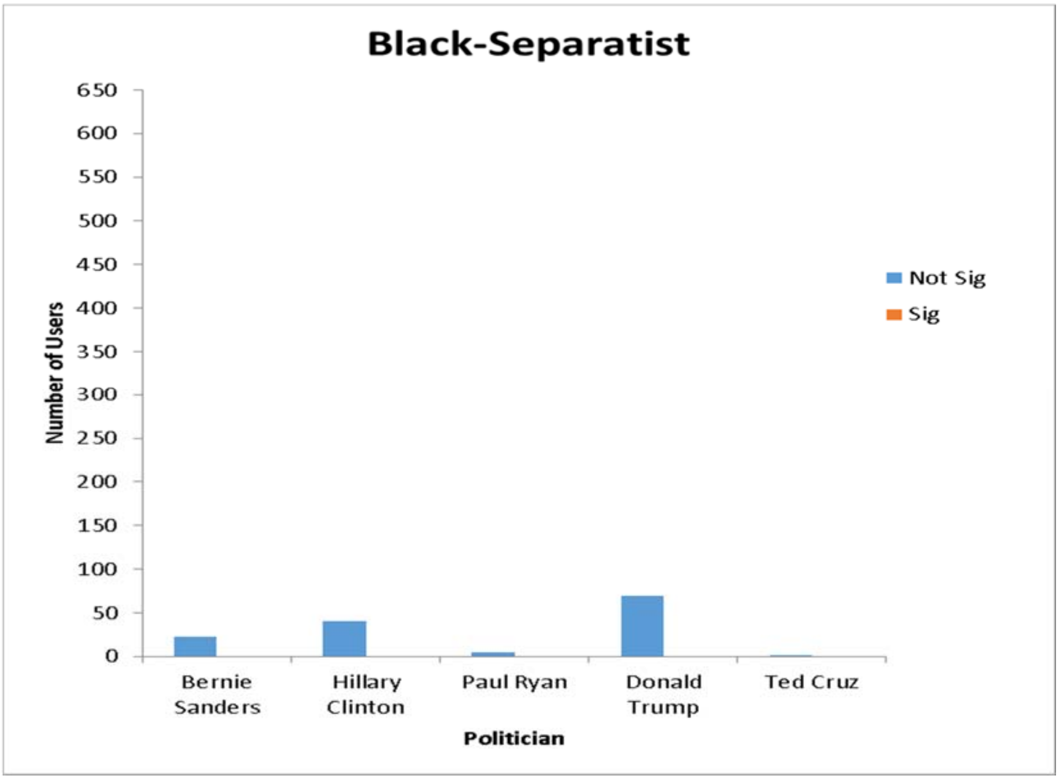

Figure 11. The number of users who retweeted the Black-Separatist groups at least five times and each of the five political leaders at least five times (*$p < 0.001$)

Discussion

Development and Program testing

The aim of this research was to establish an easy-to-implement solution to gather, analyze, and test a social/political question of interest for social and political scientists. One of the main challenges of gathering data from Twitter is the vast amounts of data available: 6000 tweets per seconds from all over the world. The data for one tweet, includes the meta data, which is exponentially larger than the tweet itself. This poses a challenge for most social and political scientists trying to pin point what is relevant to their research and what is not. The alteration of the Twitter Streaming API and gathering a random collection of users' timelines gives this research the advantage of collecting filtered data without losing its integrity or validity.

The second aim of this research was to be able to use millions of retweets to map the Twitter linkages between several American politicians from the 2016 election and American hate groups along with their leadership. The Streaming Job collected over 17 million and the Rest API Job collected close to one million. The logic developed can separate the retweet from all other forms of communication; for example: the quoted tweets, mentions and tweets. Permute and Crosswire algorithm were developed and used to find the relationship between different millions of users, who retweet the hate groups and any of the politician in our research in a small amount of time. For this aspect of the research the requirements were developed, tested and met.

Mathematical Algorithm

Permuted and cross-wired edges were developed to combine and analyze the number of times each user retweets others and is retweeted by others while preserving the observed in-and out-degrees. This method is both robust to changes and adaptable to different platforms.

Analyzing the results of hate groups' interaction with the five politicians using Twitter data indicated that Anti-Government, Neo-Nazi and White-Nationalist tweeters all significantly retweeted Trump, but not any other politician. By contrast, retweeters of Anti-Immigrant, Anti-LGBT, and Anti-Muslim groups significantly retweeted Ted Cruz, Paul Ryan, and Donald Trump. However there is a great difference between the number of Ryan and Cruz retweeters and Trump retweeters with these ideologies – Trump is retweeted to a much larger extent by people retweeting these groups.

As there was little activity recorded for Ku-Klux-Klan, Neo-Confederate, and Christian Identity groups identified by SPLC on Twitter, it was impossible to develop a conclusion about their interactions. However, retweeters of Black-Separatist groups did not significantly retweet any of the politicians used in this work suggesting that none of the five political leaders from the 2016 election had special appeal to Black-Separatist groups.

First hypothesis

The first hypothesis was that the users who retweet the SPLC hate groups' and their leaderships would retweet Donald Trump more than any other candidate. The statistically significant results indicated that most of the Anti-government, Anti-Immigrant, Anti-LGBT, Anti-Muslim, Neo-Nazi, and White Nationalist hate groups' retweeters also retweeted Donald Trump more than any other candidate. This result supports the idea that Donald Trump has a unique appeal to hate groups and bigoted individuals more than any other politician (Flitter & Kahn, 2016; Frank, 2016; The Texas Politics Project, 2016). As a result, hate groups like Ku Klux Klan (KKK) and Neo-Nazi groups supported Donald Trump's candidacy quite openly (Holley, 2016; Neiwert & Posner, 2016).

Second hypothesis

The second hypothesis was that the type of ideology of the hate group plays a role in retweeting. Specifically, we predicted that Anti Government, Anti-Immigrant, Anti Muslim, Neo-Nazi, and White Nationalist retweeters would retweet Donald Trump more than the rest of the groups because of the greater appeal of his message to their ideologies more than any other candidate. We also predicted that there was unlikely to be any difference in the amount of retweeting of Anti-LGBT, Christian identity, Neo-Confederate, and Black Separatist groups between Donald Trump and the other American political leaders as his campaign was not largely focused on promoting these ideologies. While Christian identity and Neo-Confederate groups did not have an active Twitter presence making it hard to draw any conclusions here, retweeters of Black Separatist groups were indeed unrelated to Trump or any of the other politicians, as expected. However, surprisingly, retweeters of the Anti-LGBT groups significantly retweeted Trump, Ryan, and Cruz, but were especially likely to retweet Trump more than the rest of the politicians. It may be that while Anti-LGBT retweeters endorsed all Republican candidates (as seen in the significant linkages with all 3 Republican candidates), Trump had stronger appeal as a political outsider who may be prepared to stand up for them.

Conclusion

Big Data has been a growing field, especially after Social Networks, for example, “Twitter”, allowed developers to collect data (Conover et al., 2011). This research utilises Twitter data and Apache Spark to expand and develop a statistical and easy to re- implement method to test a social/political questions. In this current research we focused on Donald Trump’s campaign for President of the USA. By examining Twitter linkages between American political leaders (Donald Trump, Hillary Clinton, Bernie Sanders, Ted Cruz, and

Paul Ryan) and American hate groups using retweet data, it was established that retweeters of various hate groups and their leaders also retweeted Donald Trump more than any other politician examined here. This research is the first to empirically examine the connection between Donald Trump and American hate groups or their leadership. These findings suggest that as some speculated, Donald Trump may have had unique appeal to a number of hate groups in America, at least more than any other politician.

This research developed a relatively easy way to collect Twitter data and fine-tune the streaming API to collect just for a particular set of Twitter accounts; this provides researchers with a relatively quick way to analyze Big Data, which could be adapted to different platforms. One of the limitations of the present work is that it relies on SPLC’s classification of American hate groups, which some have criticized (Wong, 2015; Nawaz, 2016). However, if needed, the same algorithm and analyses could be conducted if a different public database of hate groups became available for use. Future work can examine social media linkages between politicians to hate groups in various nations. Future research could also be extended to compare Donald Trump’s support before and after his election to test whether his ability to implement his promises impacts on support for hate groups. The present work provides a starting point for many such future explorations using Twitter data.

Appendix A

HATEGROUPS

by Rania Sahioun

Supervisors: Kumar Yogeeswaran (senior supervisor)

Kyle Nash (co-supervisor)

Raazesh Sainudiin (associate supervisor)

July 5, 2017

Group table

Ideology	Group Name	Founded	Twitter ID	#Follow
ANTI-IMMIGRANT	AMERICAN BORDER PATROL/AMERICAN PATROL	1992	@AmericanPatrol	1,079
ANTI-IMMIGRANT	Federation for American Immigration Reform (FAIR)	1979	@FAIRImmigration	53.2K
ANTI-IMMIGRANT	NATIONAL COALITION FOR IMMIGRATION	1994		
ANTI-IMMIGRANT	THE SOCIAL CONTRACT PRESS	1990		
Anti-LGBT	AMERICAN FAMILY ASSOCIATION	1977	@AmericanFamAssc	11.1K
Anti-LGBT	FAMILY RESEARCH COUNCIL	1983	@FRCdc	23.1K
Anti-LGBT	LIBERTY COUNSEL	1989	@libertycounsel	6,330
Anti-LGBT	TRADITIONAL VALUES COALITION	1980	@NCValues	2,345
Anti-LGBT	WESTBORO BAPTIST CHURCH	1955	@WBCSaysRepent	13.6K
Anti-Muslim	ACT! FOR AMERICA	2007	@ACTforAmerica	56.6K
Anti-Muslim	CENTER FOR SECURITY POLICY	1988	@securefreedom	6,967
Anti-Muslim	Frank Gaffney		@frankgaffney	
ANTIGOVERNMENT	WORLDNETDAILY	1999		
BLACK SEPARATIST	NATION OF ISLAM	1930	@LouisFarrakhan	457K
BLACK SEPARATIST	NEW BLACK PANTHER PARTY	1989	@NewBlackPanthr1	5,650
BLACK SEPARATIST	NUWAUBIAN NATION OF MOORS	1970	@NuwaubianMoors	78
CHRISTIAN IDENTITY	AMERICA’S PROMISE MINISTRIES	1967	@AmericasPromise	16
CHRISTIAN IDENTITY	KINGDOM IDENTITY MINISTRIES	1982		
HOLOCAUST DENIAL	INSTITUTE FOR HISTORICAL REVIEW	1978		
KU KLUX KLAN	BROTHERHOOD OF KLANS	1996	@KKK	5,496
KU KLUX KLAN	CHURCH OF THE NATIONAL KNIGHTS OF THE KU KLUX KLAN	1960	@MilitantKnights	494
KU KLUX KLAN	KNIGHTS OF THE KU KLUX KLAN	1975	@MilitantKnights	492
KU KLUX KLAN	IMPERIAL KLANS OF AMERICA	1996		
NEO-CONFEDERATE	LEAGUE OF THE SOUTH	1994	@dixienetdotorg	509
NEO-NAZI	ARYAN NATIONS	1977	@AryanNations	615
NEO-NAZI	THE CREATIVITY MOVEMENT	2004	@TCMChurch	202
NEONAZI	NATIONAL ALLIANCE	1970		
NEONAZI	NATIONAL SOCIALIST MOVEMENT	1994	@natsocialist	27K
NEONAZI	NATIONAL VANGUARD	2005	@americavanguard	984
NEONAZI	WHITE LIVES MATTER	2015	@WLMcom	168K
NEONAZI	WHITE REVOLUTION	2002		
RACIST SKINHEAD	BLOOD & HONOUR	1987	@bloodandhonour	37 prot
RACIST SKINHEAD	KEYSTONE UNITED	2001	@KeystoneUnited	244 prot
RACIST SKINHEAD	VINLANDERS SOCIAL CLUB	2003		
White Nationalist	AMERICAN FREEDOM PARTY	2009	@AFDINational	1,812
White Nationalist	AMERICAN RENAISSANCE	1990	@AmRenaissance	13.3K
White Nationalist	ARYAN BROTHERHOOD	1964	@Aryan Brother	964
White Nationalist	ARYAN BROTHERHOOD OF TEXAS	1981		
White Nationalist	BARNES REVIEW	1994	@BNReviewer	35K
White Nationalist	COUNCIL OF CONSERVATIVE CITIZEN	1985	@CofCCOhio	273

White Nationalist	EURO	2000		
White Nationalist	OCCIDENTAL QUARTERLY	2001		
White Nationalist	PIONEER FUND	1937		
White Nationalist	STORMFRONT	1995	@Stormfront txt	551
White Nationalist	TRADITIONALIST WORKERS PARTY	2015	@TradWorker	1,022
White Nationalist	VDARE	1999	@vdare	19.6K

Introduction

https://www.splcenter.org/fighting-hate/extremist-files/groups

EXTREMIST FILES Extremists in the U.S. come in many different forms white nationalists, anti-gay zealots, black separatists, racist skinheads, neo-Confederates and more.

3 ANTI-IMMIGRANT

Anti-immigrant hate groups are the most extreme of the hundreds of nativist and vigilante groups that have proliferated since the late 1990s, when anti-immigration xenophobia began to rise to levels not seen in the United States since the 1920s. https://www.splcenter.org/fighting-hate/extremist-files/ideology/anti-immigrant

3.1 AMERICAN BORDER PATROL/AMERICAN PATROL

Data gathered on 19/9/2016 from https://www.splcenter.org/fighting-hate/ extremist-files/group/american-border-patrolamerican-patrol

Date Founded: 1992 Location: Sierra Vista, AZ American Border Patrol/American Patrol (the first-listed group was essentially an Arizona extension of American Patrol, which is also known as Voice of Citizens Together) is one of the most virulent anti-immigrant groups around. On the American Patrol website and in self-produced videos, the group rails against Mexican immigrants, accusing them of bringing to the U.S. crime, drugs and squalor and of practicing immigration via the birth canal. Mexicans, in the words of group founder Glenn Spencer, are a cultural cancer following a secret plan, the Plan de Aztln, to complete la reconquista (the reconquest, or takeover) of the American Southwest, which was once controlled by Spain and/or Mexico.

Twitter account: @AmericanPatrol

TWEETS: 20.4K

FOLLOWING: 301

FOLLOWERS: 1,079

LIKES: 7

LISTS: 3

URL:https://twitter.com/americanpatrol

3.2 Federation for American Immigration Reform (FAIR)

https://www.splcenter.org/fighting-hate/extremist-files/group/federation-american-immigratio
Date Founded 1979

Location Washington, D.C.

The Federation for American Immigration Reform (FAIR) is a group with one mission: to severely limit immigration into the United States. Although FAIR maintains a veneer of legitimacy that has allowed its principals to testify in Congress and lobby the federal government, this veneer hides much ugliness. FAIR leaders have ties to white supremacist groups and eugenicists and have made many racist statements. Its advertisements have been rejected because of racist content. FAIRs founder, John Tanton, has expressed his wish that America remain a majority-white population: a goal to be achieved, presumably, by limiting the number of nonwhites who enter the country. One of the groups main goals is upending the Immigration and Nationality Act of 1965, which ended a decades-long, racist quota system that limited immigration mostly to northern Europeans. FAIR President Dan Stein has called the Act a ”mistake.”

Twitter Account @FAIRImmigration

TWEETS 21.2K

FOLLOWING 1,240

FOLLOWERS 53.2K

LIKES 2

LISTS 8 FAIR Federation for American Immigration Reform (FAIR) fights for a stronger

America with controlled borders, reduced immigration and better enforcement. #NoAmnesty Washington, DC, FAIRUS.org, Joined January 2009, National Coalition for Immigration Reform

3.3 NATIONAL COALITION FOR IMMIGRATION REFORM

https://www.splcenter.org/fighting-hate/extremist-files/group/national-coalition-immigration
The National Council for Immigration Reform is the latest incarnation of a group originally called the California Coalition for Immigration Reform, renamed after the 2013 death of founder Barbara Coe. Coe was known for referring to immigrants as savages, alleging a secret Mexican plan to reconquer the American Southwest, and claiming that immigration had led to an epidemic of rape and murder. The California Coalition for Immigration Reform (CCIR) was founded in 1994 by Barbara Coe. Its original purpose was to serve as a co-sponsor for California’s Proposition 187, which would have denied social and medical benefits to undocumented immigrants and their children. The initiative passed, but was stalled in the courts for years and effectively killed in 1998 by the then newly elected Democratic Gov. Gray Davis. In 1999, CCIR helped organize a failed effort to recall Davis, who Coe derided as ”Gov. Gray ’Red’ Davis.”

Date Founded 1994

Location Huntington Beach, Calif.

No twitter account for this group or founder BARBARA COE

3.4 THE SOCIAL CONTRACT PRESS

https://www.splcenter.org/fighting-hate/extremist-files/group/social-contract-press The Social Contract Press (TSCP) routinely publishes race-baiting articles penned by white nationalists. The press is a program of U.S. Inc, the foundation created by John Tanton, the racist founder and principal ideologue of the modern nativist movement. TSCP puts an academic veneer of legitimacy over what are essentially racist arguments about the inferiority of today's immigrants. Recent articles in its main product,

The Social Contract, have propagated the myth that Latino activists want to occupy and 'reclaim' the American Southwest, argued that no Muslim immigrants should be allowed into the U.S., and claimed that multiculturalists are trying to replace "successful Euro-American culture" with "dysfunctional Third World cultures."

Date Founded 1990

Location Petoskey, Mich.

No twitter account for this group or associated extermist profiles ASSOCIATED EXTREMIST PROFILES; Wayne Lutton (Petoskey, Mich), John Tanton (Petoskey, Mich), Kevin Lamb (Mount Airy, Maryland)

4 Anti-LGBT

Opposition to equal rights for LGBT people has been a central theme of Christian Right organizing and fundraising for the past three decades a period that parallels the fundamentalist movement's rise to political power. https://www.splcenter.org/ fighting-hate/extremist-files/ideology/anti-lgbt

4.1 @AmericanFamAssc AMERICAN FAMILY ASSOCIATION

https://www.splcenter.org/fighting-hate/extremist-files/group/american-family-association The American Family Association (AFA) says it promotes "traditional moral values" in media. A large part of that work involves "combating the homosexual agenda" through various means, including publicizing companies that have pro-gay policies and organizing boycotts against them.

Initially founded as the National Federation for Decency, the American Family Association (AFA) originally focused on what it considered indecent television programming and pornography. The AFA says it promotes "traditional moral values" in media. A large part of that work involves "combating the homosexual agenda" through various means, including publicizing companies that have pro-gay policies and organizing boycotts against them. The AFA has a variety of outlets to disseminate its message, including the American Family Radio Network, its online One News Now and the monthly AFA Journal. In early 2011, the AFA claimed more than 2 million online supporters and 180,000 subscribers to its Journal.

Date Founded 1977

Location Tupelo, Miss.

American Family AsscVerified account

Twitter Account @AmericanFamAssc

Since 1977 American Family Association has existed to inform & equip individuals to strengthen the moral foundations of American culture. Radio network: @AFRnet

Tupelo, Mississippi, afa.net, Joined May 2009

https://twitter.com/americanfamassc?lang=en TWEETS 6,404

FOLLOWING 324

FOLLOWERS 11.1K

LIKES 1,960

4.2 @FRCdc FAMILY RESEARCH COUNCIL

https://www.splcenter.org/fighting-hate/extremist-files/group/family-research-council The Family Research Council (FRC) bills itself as the leading voice for the family in our nations halls of power, but its real specialty is defaming gays and lesbians. The FRC often makes false claims about the LGBT community based on discredited research and junk science. The intention is to denigrate LGBT people in its battles against same-sex marriage, hate crimes laws, anti-bullying programs and the repeal of the militarys Dont Ask, Dont Tell policy.

To make the case that the LGBT community is a threat to American society, the FRC employs a number of policy experts whose research has allowed the FRC to be extremely active politically in shaping public debate. Its research fellows and leaders often testify before Congress and appear in the mainstream media. It also works at the grassroots level, conducting outreach to pastors in an effort to transform the culture.

Date Founded 1983 Location Washington, D.C.

FRCVerified account

Twitter Account @FRCdc

Family Research Council is America’s premier public policy org advancing faith, family, and freedom in our nation’s capital. Led by @Tperkins. #religiousfreedom Washington, DC, frc.org/twitter, Joined December 2008

TWEETS 19.8K

FOLLOWING 4,386

FOLLOWERS 23.1K

LIKES 1,991

LISTS 17 Tony Perkins @tperkins

President of @FRCdc. Host of Washington Watch with Tony Perkins. Author of #NoFearBook. Married for 30 years and proud father of five. Washington DC, tonyperkins.com, Joined January 2009 https://twitter.com/tperkins?lang=en

TWEETS 13.9K

FOLLOWING 2,573

FOLLOWERS 25.4K

LIKES 1,030

LISTS 2

4.2.1 FRCAction

@FRCAction The legislative affiliate of Family Research Council (@frcdc). Join the

#valuesbus tour at https://t.co/S3EwgvS0CV! Washington, DC frcaction.org

Joined December 2008 https://twitter.com/frcaction

TWEETS 5,369

FOLLOWING 2,124

FOLLOWERS 9,322

LIKES 231

4.2.2 Peter Sprigg

@spriggfrc Family Research Council, Senior Fellow for Policy Studies,

Washington, DC, frc.org, Joined February 2011

TWEETS 3,311

FOLLOWING 311

FOLLOWERS 1,396

LIKES 26 LISTS 1

https://twitter.com/spriggfrc?lang=en

4.2.3 Arina O. Grossu

@ArinaGrossu

Director of Center for Human Dignity, at the Family Research Council. I'm prowoman, pro-man, pro-child, pro-life. Washington DC , frc.org, Joined January 2014

TWEETS 390

FOLLOWING 458

FOLLOWERS 840

LIKES 56 https://twitter.com/arinagrossu

4.2.4 Rob Schwarzwalder

@SchwarzSpeaks Senior Vice President for Family Research Council. Washington,

D.C. , frc.org, Joined January 2011

TWEETS 1,418

FOLLOWING 1,758

FOLLOWERS 1,078

LIKES 25

LISTS 1 https://twitter.com/schwarzspeaks

4.3 @libertycounsel LIBERTY COUNSEL

https://www.splcenter.org/fighting-hate/extremist-files/group/liberty-counsel Liberty Counsel is a legal organization advocating for anti-LGBT discrimination under the guise of religious liberty. The Liberty Counsel was founded by conservative activists Mathew (Mat) Staver an attorney and former dean at Liberty University School of Law and his wife Anita. The Counsel bills itself as a non-profit litigation, education and policy organization that provides legal counsel and pro bono assistance in cases dealing with religious liberty, the sanctity of human life" and the family. Mat Staver

chairs the Counsel; his wife Anita is the president. The Liberty Counsel shares a close affiliation with Liberty University (founded by the late Jerry Falwell in Lynchburg, Va.) , especially the universitys school of law. The partnership includes the Washington, D.C.-based Liberty Center for Law and Policy, which conducts legal research and writes about current legislation and policies.

Date Founded 1989

Location Orlando, Fl.

Liberty Counsel

Twitter Account @libertycounsel

Restoring the culture by advancing religious freedom, the sanctity of human life, and the family. #ReligiousFreedom #Life #Family USA LC.org, Joined March 2009, Born in 1989

TWEETS 7,653

FOLLOWING 2,142

FOLLOWERS 6,330

LIKES 546

4.3.1 Mathew Staver

@MatStaver

Founder and Chairman of Liberty Counsel. Constitutional attorney defending life, liberty and family. Joined February 2009

TWEETS 491

FOLLOWING 707

FOLLOWERS 2,093 LIKES 115

https://twitter.com/matstaver

4.4 @NCValues TRADITIONAL VALUES COALITION

https://www.splcenter.org/fighting-hate/extremist-files/group/traditional-values-coalition

Presbyterian minister Lou Sheldon founded the Traditional Values Coalition (TVC) in 1980 to spread a moral code and behavior based upon the Old and New Testaments and to warn Americans of the rising gay threat. The traditional values the TVC fights for include: the right to life (opposition to abortion and euthanasia), chastity and patriotism, along with opposition to homosexuality, pornography, the teaching of evolution in public schools and illegal immigration. Sheldon also opposes gambling, except when he doesnt in 2000, he helped kill the Internet Gambling Prohibition Act after the TVC received a $25,000 check from eLottery, a client of now-disgraced former lobbyist Jack Abramoff. The TVC, whose president is Sheldons daughter, Andrea Lafferty, claims to represent over 43,000 Christian churches across the United States. Lafferty, who served in the Reagan and Bush administrations, is married to James Jim Lafferty, the chairman of the Coalition of Religious Freedom. The Southern Poverty Law Center has listed TVC as a hate group since 2010, based on its consistent spreading of lies about LGBT people.

Date Founded 1980

Location Anaheim, Calif., Washington, D.C.

NC Values Coalition

Twitter Account @NCValues

Pro Marriage. Pro-Life. Pro Religious Liberty. North Carolina, ncvalues.org, Joined January 2011

https://twitter.com/ncvalues

TWEETS 5,827

FOLLOWING 1,698

FOLLOWERS 2,345

LIKES 291

LISTS 3

4.5 @WBCSaysRepent WESTBORO BAPTIST CHURCH

https://www.splcenter.org/fighting-hate/extremist-files/group/westboro-baptist-church Westboro Baptist Church (WBC) is arguably the most obnoxious and rabid hate group in America. The group is basically a family-based cult of personality built around its patriarch, Fred Phelps. Typified by its slogan, God Hates Fags, WBC is known for its harsh anti-gay beliefs and the crude signs its members carry at their frequent protests.

Date Founded 1955 Location Topeka, Kan.

Twitter Account Westboro Baptist

User Name @WBCSaysRepent

The Church of the Lord Jesus Christ calls all men to repent - we are in the last days of all - time is short. Legit media contact us via @WBCMediaContact

Topeka, KS, godhatesfags.com, Joined October 2009

TWEETS 44K

FOLLOWING 39

FOLLOWERS 13.6K

LIKES 419

4.5.1 Westboro Baptist

@GodHatesFagsWBC

Official Twitter of Pastor Fred Phelps and Westboro Baptist Church in Topeka, KS Topeka, KS

GodHatesFags.Com

Joined December 2010

https://twitter.com/godhatesfagswbc

TWEETS 244

FOLLOWING 5

FOLLOWERS 8,971

4.5.2 Fred Phelps, Jr.

@WBCFredJr

Not even a close question that homosexuals control this country at all levels. Any country that accepts & promotes this sin is history. Finished. Doomed. #sodom Westboro Baptist Church godhatesfags.com Joined April 2011

TWEETS 55.6K

FOLLOWING 66

FOLLOWERS 3,575

LIKES 30

4.5.3 WBCSigns

@WBCsigns

Images, info & explanations of the world-famous pickets signs Westboro Baptist Church uses to preach. Follow our official account: @WBCSaysRepent Sidewalks, WBC Sign Shop, Vine!

GodHatesFags.com Joined April 2011 https://twitter.com/wbcsigns

TWEETS 10.1K

FOLLOWING 65

FOLLOWERS 1,698

LIKES 584

5 Anti-Muslim

https://www.splcenter.org/fighting-hate/extremist-files/ideology/anti-muslim Anti-Muslim hate groups are a relatively new phenomenon in the United States, most of them appearing in the aftermath of the World Trade Center terrorist attacks on Sept. 11, 2001. Earlier anti-Muslim groups tended to be religious in orientation and disputed Islams status as a respectable religion.

5.1 @ACTforAmerica ACT! FOR AMERICA

https://www.splcenter.org/fighting-hate/extremist-files/group/act-america Brigitte Tudor, better known as Brigitte Gabriel, founded ACT! for America in 2007 at a time when the anti-Muslim movement America was beginning to take shape in the United States. In the years since, the group has grown to become the largest grassroots anti-Muslim group in America, claiming 280,000 members and over 1,000 chapters. In the nine years since, ACT, which stands for American Congress for Truth, and its educational arm, ACT! for America Education, has grown into far and away the largest grassroots anti-Muslim group in America.

Date Founded 2007

Location Virginia Beach, Virginia

Twitter Account: ACT for America

@ACTforAmerica

We are the NRA of national security. The nation’s largest non-profit, grassroots organization devoted to promoting national security & defeating terrorism.

actforamerica.org Joined July 2010

TWEETS 9,353

FOLLOWING 1,838

FOLLOWERS 56.6K

LIKES 1,033

LISTS 4

5.1.1 Brigitte Gabriel

@ACTBrigitte

Founder of @ACTforAmerica, the nation’s largest grassroots national security organization. NYT Best-selling author, National Security expert, & guest analyst.

USA

actforamerica.org Joined April 2016

TWEETS 426

FOLLOWING 137

FOLLOWERS 7,871

LIKES 325

5.2 @securefreedom CENTER FOR SECURITY POLICY

https://www.splcenter.org/fighting-hate/extremist-files/group/center-security-policy Founded in 1988 by former Reagan administration official Frank Gaffney, Jr., The Center for Security Policy (CSP) has gone from a respected hawkish think tank focused on foreign affairs to a conspiracy-oriented mouthpiece for the growing anti-Muslim movement in the United States. Known for its accusations that a shadowy Muslim Brotherhood has infiltrated all levels of government and warnings that creeping Shariah, or Islamic religious law, is a threat to American democracy, CSPs Gaffney has called for Congressional hearings along the lines of the notorious Cold War-era House UnAmerican Activities Committee (HUAC) to expose Muslim conspiracies. CSP has even been banned from the Conservative Political Action Conference (CPAC), a premier gathering of thousands of conservatives each spring in Washington, D.C. Date Founded 1988

Location Washington DC

Twitter Account Secure Freedom

@securefreedom

Secure Freedom, formerly The Center for Security Policy, is a think tank dedicated to identifying challenges & opportunities likely to affect national security. Washington, DC securefreedom.org Joined February 2009

TWEETS 24.6K

FOLLOWING 2,165

FOLLOWERS 6,967

LIKES 841

5.2.1 Jim Hanson

@Uncle Jimbo Exec VP at Center for Security Policy & CounterJihad. Former Army Special Forces, so expect precision fire. Arlington, VA securefreedom.org Joined August 2008

TWEETS 42.7K

FOLLOWING 7,245

FOLLOWERS 9,200

LIKES 2,216

LISTS 1

5.2.2 Frank Gaffney

@frankgaffney

Founder and President of the Center for Security Policy and host of Secure Freedom

Radio

Washington, DC securefreedom.org Joined June 2009

TWEETS 24.4K

FOLLOWING 2,589

FOLLOWERS 17.6K

LIKES 2,920

LISTS 1

6 ANTIGOVERNMENT MOVEMENT

https://www.splcenter.org/fighting-hate/extremist-files/ideology/antigovernment

The antigovernment movement has experienced a resurgence, growing quickly since

2008, when President Obama was elected to office. Factors fueling the antigovernment

movement in recent years include changing demographics driven by immigration, the struggling economy and the election of the first African-American president.

6.1 WORLDNETDAILY

https://www.splcenter.org/fighting-hate/extremist-files/group/worldnetdaily WorldNetDaily is an online publication founded and run by Joseph Farah that claims to pursue truth, justice and liberty. But in fact, its pages are devoted to manipulative fear-mongering and outright fabrications designed to further the paranoid, gay-hating, conspiratorial and apocalyptic visions of Farah and his hand-picked contributors from the fringes of the far-right and fundamentalist worlds. Among its enduring storylines is the ”birther” theory advanced by columnist Jerome Corsi, who asserts that President Obama is ineligible to serve because he was not born in America, a baseless claim long since abandoned by most of the political right.

Date Founded 1999

Location Centreville, Va.

No Twitter account had been found for this group

7 BLACK SEPARATIST

https://www.splcenter.org/fighting-hate/extremist-files/ideology/black-separatist Black separatists typically oppose integration and racial intermarriage, and they want separate institutions – or even a separate nation – for blacks. Most forms of black separatism are strongly anti-white and anti-Semitic, and a number of religious versions assert that blacks are the Biblical ”chosen people” of God.

7.1 @LouisFarrakhan NATION OF ISLAM

https://www.splcenter.org/fighting-hate/extremist-files/group/nation-islam Since its founding in 1930, the Nation of Islam (NOI) has grown into one of the wealthiest and best-known organizations in black America. Its theology of innate black superiority over whites and the deeply racist, anti-Semitic and anti-gay rhetoric of its leaders have earned the NOI a prominent position in the ranks of organized hate.

Since its founding in 1930, the Nation of Islam (NOI) has grown into one of the wealthiest and best-known organizations in black America, offering numerous programs and events designed to uplift African Americans. Nonetheless, its bizarre theology of innate black superiority over whites a belief system vehemently and consistently rejected by mainstream Muslims and the deeply racist, anti-Semitic and anti-gay rhetoric of its leaders, including top minister Louis Farrakhan, have earned the NOI a prominent position in the ranks of organized hate. Date Founded 1930// Location Chicago, IL// Twitter Account

7.1.1 @NationofIslamUK Nation of Islam UK

@NationofIslamUK The Official Twitter page representing The UK Headquarters of The Nation of Islam, Muhammad Mosque #1 located in Brixton, South London. London, England// NOI.ORG.UK// Joined January 2013// @NationofIslamUK// TWEETS 1,699// FOLLOWING 616// FOLLOWERS 856// LIKES 697//

7.1.2 @LouisFarrakhan MINISTER FARRAKHAN

@LouisFarrakhan The Official Twitter Page of The Honorable Minister Louis Farrakhan. Like Farrakhan on http://Facebook.com/OfficialMinisterFarrakhan — IG:http://Instagram.com/LouisFarrakhan Chicago, IL noi.org/hon-minister-f Joined

March 2011 Tweet to MINIST

TWEETS 7,588

FOLLOWERS 457K LIKES 180

7.1.3 @OfficialNOI The Nation of Islam

@OfficialNOI Official Nation of Islam twitter account. NOI.org Joined June 2011

TWEETS 707

FOLLOWING 4

FOLLOWERS 18.6K

7.1.4 @NOIjeffcitymo Nation of Islam

@NOIjeffcitymo Nation of Islam : Student Study Group, Jefferson City — Students of the Hon.@LouisFarrakhan — Governed by@Mosque28 in St. Louis, Student Min.

Donald Muhammad Jefferson City, MO.

NOI.org

Joined September 2014

Tweet to Nation of Isla

TWEETS 377

FOLLOWING 443

FOLLOWERS 192 LIKES 65

7.1.5 @NOI Youth NOIYouthCouncil

@NOI Youth A movement used to unite the youth, events concerning youth, throughout the regions in the Nation of Islam find us athttp://www.NOIYC.org get involved!! youthcouncilconnect@gmail.com NOIYC.org Joined July 2012 TWEETS 5,461

FOLLOWING 818

FOLLOWERS 3,395

LIKES 2

7.1.6 @JoinNationIslam Join Nation of Islam

@JoinNationIslam Will You Join The Nation of Islam?Call 773-324-6000 http://www.noi.org/join/ http://www.thenationsprogram.com/signup/ http://www.noi.org/donate.shtml Accept Your

Own & Be Yourself youtube.com/jointhenationo Joined February 2009 TWEETS 669

FOLLOWING 2,612

FOLLOWERS 2,662

LIKES 21

LISTS 28

7.1.7 @TheFinalCall The Final Call News

@TheFinalCall The Final Call Newspaper is known for hard-hitting and uncompromised reporting. Founded by Minister@LouisFarrakhan. Visit @ http://www.finalcall.com

Chicago, IL USA finalcall.com Joined April 2009 TWEETS 29K// FOLLOWING 34//

FOLLOWERS 46K// LIKES 9// LISTS 1//

7.1.8 @brotherabdul Abdul Muhammad

@brotherabdul Student Minister of the Honorable Minister Louis Farrakhan and the

Nation of Islam. #StopTheKillingTour emtecfilms.com Joined September 2010 TWEETS

5,489

FOLLOWING 124

FOLLOWERS 6,094

LIKES 130

7.2 @NewBlackPanthr1 NEW BLACK PANTHER PARTY

https://www.splcenter.org/fighting-hate/extremist-files/group/new-black-panther-party The New Black Panther Party is a virulently racist and anti-Semitic organization whose leaders have encouraged violence against whites, Jews and law enforcement officers. Founded in Dallas, the group today is especially active on the East Coast, from Boston to Jacksonville, Fla. The group portrays itself as a militant, modern-day expression of the black power movement (it frequently engages in armed protests of alleged police brutality and the like), but principals of the original Black Panther Party of the 1960s and 1970s a militant, but non-racist, left-wing organization have rejected the new Panthers as a ”black racist hate group” and contested their hijacking of the Panther name and symbol.

Date Founded 1989 Location Washington, D.C.

Twitter Account NewBlackPantherParty @NewBlackPanthr1 The Official Twitter

Page of the New Black Panther Party Reach us at: 347-903-0886 Chairman: Min.

Hashim Nzinga newblackpanther.com Joined December 2009 TWEETS 2,579

FOLLOWING 1,558

FOLLOWERS 5,650

LIKES 17

7.2.1 NEW BLACK PANTHERS

@NBPPstlouis Official Account: NEW BLACK PANTHER PARTY — CENTRAL REGION (ST. LOUIS, MO.) — #FreedomOrDeath. For more info contact Regional

Chairman D. Hawkins @ 314-599-4591 Central Region, USA NBPPCentralRegion.com

Joined January 2015

TWEETS 288

FOLLOWING 206

FOLLOWERS 442 LIKES 23

7.2.2 HASHIM A NZINGA

@HASHIMNZINGA I am the National Chairman of the New Black Panther Party for Self Defense- Dedicated to serving the people whole body and soul. Atlanta, GA newblackpanther.org Joined March 2014 TWEETS 113

FOLLOWING 260

FOLLOWERS 655

7.3 @NuwaubianMoors NUWAUBIAN NATION OF MOORS

https://www.splcenter.org/fighting-hate/extremist-files/group/nuwaubian-nation-moors Originally a putatively Muslim group, Nuwaubianism is best understood as a cult that promotes a bizarre and complicated theology.

Nuwaubians refer to their belief system which mixes black supremacist ideas with worship of the Egyptians and their pyramids, a belief in UFOs and various conspiracies related to the Illuminati and the Bilderbergers, as Nuwaubianism not as theology, but as factology, Right Knowledge, or a slew of other names. The groups founder and leader, Dwight York, took extreme advantage of its adherents, sexually abusing their children and conning the adults out of their possessions. In April 2004, he was sentenced to 135 years in prison for molesting children, among other crimes. Date Founded 1970

Location Georgia

Nuwaubian Moors

@NuwaubianMoors

We’re a Nation Of Nuwaubian Moors. Our Tribe is of INDIGENOUS PEOPLES; The Yamassee Tribe of Native American Moors. Who’s Culture is NUWAUBU (Nu-WahBu)

Atlan-Land Of The Frogs unnm.org

Joined March 2011

@NuwaubianMoors TWEETS 17 FOLLOWERS 78

7.3.1 Nuwaubian Moors

@NuwaubianNation Get the latest from the United Nuwaubian Nation of Moors of the World. Retweets do not mean endorsement. Atlanta, GA unnm.org

Joined November 2013

8 CHRISTIAN IDENTITY

Christian Identity is a unique anti-Semitic and racist theology that rose to a position of commanding influence on the racist right in the 1980s. ”Christian” in name only, the movement’s relationship with evangelicals and fundamentalists has generally been hostile due to the latters belief that the return of Jews to Israel is essential to the fulfillment of end-time prophecy.

8.1 AMERICA’S PROMISE MINISTRIES

https://www.splcenter.org/fighting-hate/extremist-files/group/americas-promise-ministries America’s Promise Ministry is both a Christian Identity church and a major publisher and distributor of right-wing extremist tracts. Located in a section of the Pacific Northwest that was a notorious hotbed of white supremacist activity in the 1990s, America’s Promise Ministry is both a Christian Identity church and a major publisher and distributor of right-wing extremist tracts. Its current leader, Dave Barley, peddles a ”soft” version of Christian Identity, one that promotes white separatism and contempt for Jews and non-whites, but that stops short of openly advocating bloodshed. Nevertheless, several of Barley’s congregants have committed serious violent crimes, including bank robberies and terrorist bombings. Date Founded 1967

Location Sandpoint, Idaho

America’s PromiseVerified account

@AmericasPromise

Building a #GradNation. Moderator of#PromiseChat. #Recommit2Kids#5Promises to #youth: #CaringAdults,#SafePlaces, #HealthyStart,#EffectiveEDU #Opps2Serve Washington, DC americaspromise.org Joined October 2009

FOLLOWING 9

FOLLOWERS 16

8.2 KINGDOM IDENTITY MINISTRIES

https://www.splcenter.org/fighting-hate/extremist-files/group/kingdom-identity-ministries

Kingdom Identity Ministries is the largest supplier in existence of materials related to Christian Identity, a radical-right theology that generally identifies people of color as soulless sub-humans and Jews as satanic or cursed by God.

It functions primarily as a publishing house, churning out Identity Bible study courses, tracts and books, including foundational texts by early Identity leaders like Wesley Swift. The ministry teaches that Judgment Day will arrive in the form of a sanctified race war, a theory widely popular with prison-based racist gangs like the

Aryan Brotherhood. Date Founded 1982

Location Harrison, AR

No Twitter Account found

9 HOLOCAUST DENIAL

https://www.splcenter.org/fighting-hate/extremist-files/ideology/holocaust-denial

Deniers of the Holocaust, the systematic murder of around 6 million Jews in World War II, either deny that such a genocide took place or minimize its extent. These groups (and individuals) often cloak themselves in the sober language of serious scholarship, call themselves historical revisionists instead of deniers, and accuse their critics of trying to squelch open-minded inquiries into historical truth.

9.1 INSTITUTE FOR HISTORICAL REVIEW

https://www.splcenter.org/fighting-hate/extremist-files/group/institute-historical-review

Founded in 1978 by Willis Carto, a longtime anti-Semite, the Institute for Historical Review (IHR) is a pseudo-academic organization that claims to seek ”truth and accuracy in history,” but whose real purpose is to promote Holocaust denial and defend Nazism. Once a prominent voice in extremist circles, the IHR has been on the decline, unable to publish its anti-Semitic Journal of Historical Review or sponsor major international Holocaust denial conferences since 2004. The organization still runs its website, where it peddles extremist books and other materials, and hosts some minor extremist gatherings.

Date Founded 1978

Location Newport Beach, CA No Twitter Account

10 KU KLUX KLAN

https://www.splcenter.org/fighting-hate/extremist-files/ideology/ku-klux-klan

The Ku Klux Klan, with its long history of violence, is the most infamous and oldest

of American hate groups. Although black Americans have typically been the Klan’s primary target, it also has attacked Jews, immigrants, gays and lesbians and, until recently, Catholics.

10.1 @KKK com BROTHERHOOD OF KLANS

https://www.splcenter.org/fighting-hate/extremist-files/group/brotherhood-klans

The Brotherhood of Klans (BOK) has long been one of the largest and most widespread Ku Klux Klan organizations in the United States. Its also the only KKK faction to establish chapters outside the U.S., with a sizable presence in Canada. Where most present-day Klan groups splash pictures and news of their activities on their websites and online forums, the Brotherhood of Klans is exceptionally secretive, in the tradition of Klan groups of yesteryear, offering scant details of its actions online and conducting serious background checks of prospective members. In other ways, the BOK is quite modern. Its members often eschew white robes and hoods for paramilitary garb, and its leadership networks extensively with non-Klan white supremacists, most notably racist skinheads and outlaw bikers, as well as with other Klan outfits, especially those based in the Deep South. Date Founded 1996

Location Marion, OH

Ku Klux Klan

@KKK com

KKK, Ku Klux Klan, White Power KKK America kkk.com

Joined August 2009

TWEETS 4

FOLLOWING 66

FOLLOWERS 5,496

10.1.1 Ku Klux Klan

@kkkofficial

Ku Klux Klan. Americas Invisible Empire. Everywhere. kukluxklan.bz Joined April 2009

TWEETS 39

FOLLOWING 3

FOLLOWERS 3,662

10.1.2 Ku Klux Klan

@KKKlan

KKK, Ku Klux Klan

KKK

kkklan.com

Joined August 2009

TWEETS 10

FOLLOWING 78

FOLLOWERS 1,083

10.2 CHURCH OF THE NATIONAL KNIGHTS OF THE KU KLUX KLAN

https://www.splcenter.org/fighting-hate/extremist-files/group/church-national-knights-ku-kl Once one of the largest and most active Klan groups in America, the Church of the National Knights of the Ku Klux Klan has more recently gained a kind of ”Keystone Kops” reputation on the white supremacist scene for its bumbling ways. As disorganized as the Indiana-based group may be, it is still dangerous, as evidenced by a 2001 murder and plot linked to National Knights members in North Carolina. Date Founded 1960 Location South Bend, IN Militant Knights KKK @MilitantKnights We are an action-oriented Racial and Political Brotherhood that is inspired and motivated by the heroic deeds and sublime beliefs of the ORIGINAL KKK

The True Invisible Empire sites.google.com/site/militantk Joined April 2009 TWEETS

125

FOLLOWING 335

FOLLOWERS 494 LIKES 20

10.3 KNIGHTS OF THE KU KLUX KLAN

https://www.splcenter.org/fighting-hate/extremist-files/group/knights-ku-klux-klan KNIGHTS OF THE KU KLUX KLAN Founded by David Duke in 1975, the Knights of the Ku Klux Klan has attempted to put a ”kinder, gentler” face on the Klan, courting media attention and attempting to portray itself as a modern ”white civil rights” organization. But beneath that veneer lurks the same bigoted rhetoric. Date Founded 1975 Location Harrison, AR Militant Knights KKK @MilitantKnights We are an actionoriented Racial and Political Brotherhood that is inspired and motivated by the heroic deeds and sublime beliefs of the ORIGINAL KKK

The True Invisible Empire sites.google.com/site/militantk Joined April 2009

Tweet to Militant Knight

TWEETS 125

FOLLOWING 335

FOLLOWERS 492

LIKES 20

10.4 IMPERIAL KLANS OF AMERICA

https://www.splcenter.org/fighting-hate/extremist-files/group/imperial-klans-america

Until the late 2000s the second largest Klan group in the nation, the Imperial Klans of America (IKA) today is smaller but remains active despite a $2.5 million judgment against its leader and several followers in a lawsuit brought by the Southern Poverty Law Center in 2008. IKA's headquarters and compound in Dawson Springs, Ky., have long served as the venue for the hate-rock gathering Nordic Fest. Date Founded 1996 Location Dawson Springs, KY No Twitter Account

11 NEO-CONFEDERATE

https://www.splcenter.org/fighting-hate/extremist-files/ideology/neo-confederate The term neo-Confederacy is used to describe twentieth and twenty-first century revivals of pro-Confederate sentiment in the United States. Strongly nativist, neo-Confederacy claims to pursue Christianity and heritage and other supposedly fundamental values that modern Americans are seen to have abandoned.

11.1 LEAGUE OF THE SOUTH

https://www.splcenter.org/fighting-hate/extremist-files/group/league-south The League of the South is a neo-Confederate group that advocates for a second Southern secession and a society dominated by European Americans. The league believes the godly nation it wants to form should be run by an Anglo-Celtic (read: white) elite. Date Founded 1994 Location Killen, Ala. League of the South @dixienetdotorg We seek to advance the cultural, social, economic, and political well-being and independence of the Southern people by all honourable means.

Killen, Alabama dixienet.org Joined April 2009

TWEETS 7

FOLLOWERS 509

12 NEO-NAZI

https://www.splcenter.org/fighting-hate/extremist-files/ideology/neo-nazi Neo-Nazi groups share a hatred for Jews and a love for Adolf Hitler and Nazi Germany. While they also hate other minorities, gays and lesbians and even sometimes Christians, they perceive ”the Jew” as their cardinal enemy.

12.1 ARYAN NATIONS

https://www.splcenter.org/fighting-hate/extremist-files/group/aryan-nations

Aryan Nations (AN) was once a powerful organizing force for white supremacists that cultivated a wide spectrum of racist and anti-Semitic ideas. Date Founded 1977 Location Chillicothe, Ohio Aryan Nations World @AryanNations We are a White Nationalist Christian Identity church. We are fighting for our folk and for unity of our folk http://bit.ly/29I50GL

Louisiana, USA aryannationsworldwide1488.org Joined May 2016 TWEETS 1,777

FOLLOWING 529

FOLLOWERS 615 LIKES 363

12.1.1 @AR1488UK

)))AryanRevolution((@AR1488UK Encouraging & Supporting National Socialism in UK we stand for white pride and wish to unite Europeans around the globe. Down with Communism Down with Zionism!

UK Joined June 2015 TWEETS 18.8K FOLLOWING 813 FOLLOWERS 3,803 LIKES 3,115

12.1.2 @whitebriton

Aryan Brotherhood UK @whitebriton ’In Nature there is NO equality & NO inequality’ G.K Chesterton - We’re NOT Racists we’re Racial Realists

UK Visit our blog below: newwhitewarrior.wordpress.com Joined June 2015 TWEETS

1,646 FOLLOWING 1,614 FOLLOWERS 2,358 LIKES 394

12.2 THE CREATIVITY MOVEMENT

https://www.splcenter.org/fighting-hate/extremist-files/group/creativity-movement The Creativity Movement is the latest of several incarnations of the racist group (and religion) originally known as Church of the Creator. The movement promotes what it sees as the inherent superiority and creativity of the white race. Date Founded 2004 Location Zion, Ill. Creativity Movement @TCMChurch A progressive, Pro-White Religious Creed.

Right behind you creativitymovement.net Joined September 2010 TWEETS 37

FOLLOWING 53

FOLLOWERS 202

12.3 NATIONAL ALLIANCE

https://www.splcenter.org/fighting-hate/extremist-files/group/national-alliance The National Alliance (NA) was for decades the most dangerous and best organized neo-Nazi formation in America. Explicitly genocidal in its ideology, NA materials call for the eradication of the Jews and other races and the creation of an all-white homeland. Date Founded 1970 Location Mill Point, WV No twitter account

12.4 NATIONAL SOCIALIST MOVEMENT

https://www.splcenter.org/fighting-hate/extremist-files/group/national-socialist-movement An organization that specializes in theatrical and provocative protests, the National Socialist Movement (NSM) is one of the largest and most prominent neo-Nazi groups in the United States. Date Founded 1994 Location Detroit, Mich. national socialist

@natsocialist NATIONAL SOCIALIST PARTY page.is/national-socia Joined December 2013 TWEETS 92.2K

FOLLOWING 2,404

FOLLOWERS 27K

LIKES 3,034

LISTS 3

12.4.1 National Socialism

@TheNaziEra Memories of the National Socialism 1921-1945

Joined June 2013 TWEETS 536 FOLLOWING 4 FOLLOWERS 981 LIKES 4

12.4.2 American Nazi Party

American Nazi Party @ANP14 The American Nazi Party is America’s premier 21st

Century National Socialist Organization. http://www.ANP14.com from sea to sea anp14.com Joined June 2010

12.5 NATIONAL VANGUARD

https://www.splcenter.org/fighting-hate/extremist-files/group/national-vanguard Formed in 2005 by longtime activist Kevin Strom, National Vanguard was a breakaway group from the neo-Nazi National Alliance. National Vanguard was increasing its membership before the arrest and imprisonment of its leader, Kevin Strom, in 2007 for child pornography and witness tampering, after which the group fell apart. Date Founded 2005 Location Charlottesville, Va. American Vanguard @americavanguard Join the Vanguard: The new face of patriotism. Young White Americans defending our race and nation against all enemies, foreign and domestic.

United States american-vanguard.org Joined January 2016 Born on July 04 TWEETS 693

FOLLOWING 133

FOLLOWERS 984 LIKES 5,195

12.6 WHITE LIVES MATTER

https://www.splcenter.org/fighting-hate/extremist-files/group/white-lives-matter

White Lives Matter, a racist response to the civil rights movement Black Lives Mat-

ter, is a neo-Nazi group that is growing into a movement as more and more white supremacist groups take up its slogans and tactics.

Date Founded 2015 Ideology Neo-Nazi WhiteLivesMattercom Twittter account @WLMcom The West can't be a welfare refuge for the failed nations of the world. Immigrants shouldn't make us dumber or poorer. See the website for educational videos.

Forced Diversity Zones whitelivesmatter.com Joined December 2015 TWEETS

1,530 FOLLOWING 245 FOLLOWERS 168K LIKES 703 LISTS 2

12.7 WHITE REVOLUTION

https://www.splcenter.org/fighting-hate/extremist-files/group/white-revolution White Revolution is a neo-Nazi group that employs the most violent language and works with some of the most virulent leaders in the world of white supremacy, while claiming to remain legal. It has sought to unite groups across the radical spectrum, but has been singularly unsuccessful. Date Founded 2002 Location Russellville, AR No twitter account was found

13 RACIST SKINHEAD

https://www.splcenter.org/fighting-hate/extremist-files/ideology/racist-skinhead Racist Skinheads form a particularly violent element of the white supremacist movement, and have often been referred to as the ”shock troops” of the hoped-for revolution. The classic Skinhead look is a shaved head, black Doc Martens boots, jeans with suspenders and an array of typically racist tattoos.

13.1 BLOOD & HONOUR

https://www.splcenter.org/fighting-hate/extremist-files/group/blood-honour Based in the United Kingdom, Blood & Honour is a shadowy international coalition of racist skinhead gangs. In the United States, two rival groups claim to be affiliated with Blood & Honour. Date Founded 1987 Blood and HonourProtected Tweets @bloodandhonour Blood and Honour / Blut und Ehre

Global bloodandhonour.com Joined June 2010

@bloodandhonour

FOLLOWING 64 FOLLOWERS 37 Protected account

13.2 KEYSTONE UNITED

https://www.splcenter.org/fighting-hate/extremist-files/group/keystone-united Keystone United, known until 2009 as the Keystone State Skinheads (KSS), is one of the largest and most active single-state racist skinhead crews in the country. Date

Founded 2001 Location Harrisburg, PA Keystone United @KeystoneUnited http://KeystoneUnited.tumblr.com

Pennsylvania Keystone-United.com Joined March 2015 TWEETS 277 FOLLOWING 191 FOLLOWERS 244 LIKES 115 This account is protected

13.3 VINLANDERS SOCIAL CLUB

https://www.splcenter.org/fighting-hate/extremist-files/group/vinlanders-social-club The Vinlanders Social Club was formed in 2003 by a handful of former members and associates of a rogue racist skinhead group, the Outlaw Hammerskins. Publicly the Vinlanders appeared to be a coalition of independent state skinhead crews, but in reality the group functioned as a single entity. No Twitter Account was find

14 White Nationalist

https://www.splcenter.org/fighting-hate/extremist-files/ideology/white-nationalist White nationalist groups espouse white supremacist or white separatist ideologies, often focusing on the alleged inferiority of nonwhites. Groups listed in a variety of other categories - Ku Klux Klan, neo-Confederate, neo-Nazi, racist skinhead, and Christian Identity - could also be fairly described as white nationalist.

14.1 AMERICAN FREEDOM PARTY

https://www.splcenter.org/fighting-hate/extremist-files/group/vinlanders-social-club The American Freedom Party (formerly American Third Position) is a political party initially established by racist Southern California skinheads that aims to deport immigrants and return the United States to white rule. Date Founded 2009 Location Las Vegas, Nevada AFDI @AFDINational Official page of American Freedom Defense Initiative, a human rights organization dedicated to freedom of speech, freedom of conscience and individual rights.

Joined August 2011

@AFDINational

TWEETS 20.8K FOLLOWING 13 FOLLOWERS 1,812 LIKES 3

14.2 AMERICAN RENAISSANCE

Founded by Jared Taylor in 1990, the New Century Foundation is a self-styled think tank that promotes pseudo-scientific studies and research that purport to show the inferiority of blacks to whites. It is best known for its American Renaissance magazine and website. American Renaissance @AmRenaissance America’s premier source for race-realist thought. Oakton, Virginia amren.com Joined June 2011 TWEETS 939 FOLLOWING 121 FOLLOWERS 13.3K

14.3 ARYAN BROTHERHOOD

https://www.splcenter.org/fighting-hate/extremist-files/group/aryan-brotherhood The Aryan Brotherhood, also known as The Brand, Alice Baker, AB or One-Two, is the nations oldest major white supremacist prison gang and a national crime syndicate. Founded in 1964 by Irish bikers as a form of protection for white inmates in newly desegregated prisons, the AB is today the largest and deadliest prison gang in the United

States, with an estimated 20,000 members inside prisons and on the streets. Aryan

Brotherhood @Aryan Brother Official Sanctioned Twitter of the Aryan Brotherhood D.O.C newsaxon.org/group/aryan-br Joined June 2013

@Aryan Brother TWEETS 43 FOLLOWING 125 FOLLOWERS 964 LIKES 47

14.3.1 Aryan Brotherhood UK

Aryan Brotherhood UK @whitebriton ’In Nature there is NO equality & NO inequality’ G.K Chesterton - We’re NOT Racists we’re Racial Realists

UK Visit our blog below: newwhitewarrior.wordpress.com Joined June 2015

14.4 ARYAN BROTHERHOOD OF TEXAS

https://www.splcenter.org/fighting-hate/extremist-files/group/aryan-brotherhood-texas Founded in the early 1980s, the Aryan Brotherhood of Texas, also known as the ABT, the Tip and Ace Deuce, is an unrelated knockoff of the racist prison gang Aryan Brotherhood. It is one of the deadliest prison gangs in the Texas Department of Prisons, and also a statewide crime syndicate. Like the Aryan Brotherhood, the ABT has a strictly hierarchical leadership structure and has members both inside the states prisons and on the streets. Date Founded 1981 No twitter account

14.5 BARNES REVIEW

https://www.splcenter.org/fighting-hate/extremist-files/group/barnes-review Founded by Willis Carto in 1994, The Barnes Review (TBR) is one of the most virulent anti-Semitic organizations around. Its flagship journal, The Barnes Review, and its website, Barnesreview.org, are dedicated to historical revisionism and Holocaust denial. The B&N Review @BNReviewer Dispatches and (mostly) literary distractions from the editors of the Barnes and Noble Review.

NYC bnreview.com Joined June 2008 TWEETS 6,395 FOLLOWING 1,464 FOLLOWERS 35K LIKES 1,959 LISTS 1

14.6 COUNCIL OF CONSERVATIVE CITIZENS

https://www.splcenter.org/fighting-hate/extremist-files/group/council-conservative-citizens

The Council of Conservative Citizens (CCC) is the modern reincarnation of the old White Citizens Councils, which were formed in the 1950s and 1960s to battle school desegregation in the South. Created in 1985 from the mailing lists of its predecessor organization, the CCC has evolved into a crudely white supremacist group. Date Founded 1985 Location St. Louis, MO C of CC OHIO @CofCCOhio Council of Conservative Citizens - OHIO #AltRight

#14W #WPWW #2A #tcot We must secure the existence of our people & the future for White Children - David Lane

Ohio, USA CofCCOhio.org Joined February 2013 TWEETS 14.8K FOLLOWING 406 FOLLOWERS 273 LIKES 397 LISTS 1

14.7 EURO

https://www.splcenter.org/fighting-hate/extremist-files/group/euro Founded in 2000 under a different name by the former Klan leader and notorious neoNazi David Duke, the European-American Unity and Rights Organization (EURO) claims to fight for ”White Civil Rights” for ”European and Americans Wherever They

May Live.” Date Founded 2000 Location Mandeville, LA

No twitter account

14.8 OCCIDENTAL QUARTERLY

https://www.splcenter.org/fighting-hate/extremist-files/group/occidental-quarterly

Founded in 2001 by Chicago millionaire publishing scion William H. Regnery, the Charles Martel Society publishes The Occidental Quarterly (TOQ), a racist journal devoted to the idea that as whites become a minority ”the civilization and free governments that whites have created” will be jeopardized. Date Founded 2001 Location Atlanta, GA No twitter account

14.9 PIONEER FUND

https://www.splcenter.org/fighting-hate/extremist-files/group/pioneer-fund Started in 1937 by textile magnate Wickliffe Draper, the Pioneer Fund’s original mandate was to pursue ”race betterment” by promoting the genetic stock of those ”deemed to be descended predominantly from white persons who settled in the original thirteen states prior to the adoption of the Constitution.” Date Founded 1937 Location New York, NY No twitter account

14.10 STORMFRONT

https://www.splcenter.org/fighting-hate/extremist-files/group/stormfront

Created by former Alabama Klan boss and long-time white supremacist Don Black in 1995, Stormfront was the first major hate site on the Internet. Claiming more than 300,000 registered members as of May 2015 (though far fewer remain active), the site has been a very popular online forum for white nationalists and other racial extremists. Date Founded 1995 Location West Palm Beach, FL Stormfront.txt @Stormfront txt Real posts direct from stormfront, the racist front page of the internet Joined May 2013

TWEETS 45 FOLLOWING 7 FOLLOWERS 551 LIKES 1

14.11 TRADITIONALIST WORKERS PARTY

https://www.splcenter.org/fighting-hate/extremist-files/group/traditionalist-workers-party The Traditionalist Workers Party is a white nationalist group that advocates for racially pure nations and communities and blames Jews for many of the worlds problems. Even as it claims to oppose racism, saying every race deserves its own lands and culture, the group is intimately allied with neo-Nazi and other hardline racist organizations that

espouse unvarnished white supremacist views. Date Founded 2015 Location Cincinnati, Ohio TradWorker @TradWorker Traditionalist Worker Party Local solutions to the globalist problem. This is the official account of the Traditionalist Worker Party. United States tradworker.org Joined October 2015 TWEETS 567 FOLLOWING 88 FOLLOWERS 1,022 LIKES 124

14.12 VDARE

https://www.splcenter.org/fighting-hate/extremist-files/group/vdare Originally established in 1999 by the Center for American Unity, a Virginia-based nonprofit foundation started by English immigrant Peter Brimelow, VDARE.com is an anti-immigration hate website ”dedicated to preserving our historical unity as Americans into the 21st Century.” Date Founded 1999 Location Washington, Conn.

Virginia Dare @vdare The Twitter account for the editors of VDARE Featured at the 2016 Republican National Convention vdare.com Joined March 2009 TWEETS

23.8K FOLLOWING 4,518 FOLLOWERS 19.6K LIKES 10K

Other users added to the SPLC list on 7/11/2016. Data collected on the 30/11/2016

15 Alt-Right @ AltRight (suspended) AmRenaissance

Twitter account American Renaissance @AmRenaissance America’s premier source for race-realist thought.

Oakton, Virginia amren.com Joined June 2011 TWEETS 1,091 FOLLOWING 115 FOLLOWERS 15.1K LIKES 2

15.1 RICHARD BERTRAND SPENCER

https://www.splcenter.org/fighting-hate/extremist-files/individual/ richard-bertrand-spencer-0 As head of the National Policy Institute (NPI), Richard Spencer is one of the countrys most successful young white nationalist leaders a suitand-tie version of the white supremacists of old, a kind of professional racist in khakis. Twitter Account@RichardBSpencer (suspended)

15.2 Jared Taylor

https://www.splcenter.org/fighting-hate/extremist-files/individual/ jared-taylor In his personal bearing and tone, Jared Taylor projects himself as a courtly presenter of ideas that most would describe as crudely white supremacist a kind of modern-day version of the refined but racist colonialist of old. Twitter Account Jared Taylor @jartaylor Editor of American Renaissance. Author of White Identity: Racial Consciousness in the 21st Century. Oakton, Virginia, USA amren.com Joined

March 2011 TWEETS 1,250 FOLLOWING 27 FOLLOWERS 20.4K

15.3 Greg Johnson

Twitter Account Counter-Currents @NewRightAmerica Counter-Currents Publishing, home of the North American New Right, Books Against Time, and Counter-

Currents Radio

San Francisco counter-currents.com Joined June 2010 TWEETS 6,315 FOLLOWING 46 FOLLOWERS 8,177 LIKES 256

15.4 Matthew Parrott

TradYouth @TradYouth Faith, Family, and Folk against the Modern world!

USA tradyouth.org Joined May 2013 TWEETS 4,321 FOLLOWING 1,311 FOLLOWERS 4,140 LIKES 1,502

15.5 MATTHEW HEIMBACH

https://www.splcenter.org/fighting-hate/extremist-files/individual/ matthew-heimbach Considered by many to be the face of a new generation of white nationalists, Matthew Heimbach founded a campus chapter of Youth for Western Civilization at Towson University in Maryland and later started the White Student Union there. He also has been a member of the neo-Confederate League of the South. Since graduating in the spring of 2013, he has entrenched himself further in the white nationalist movement and become a regular speaker on the radical-right lecture circuit. Twitter Account Matthew HeimbachVerified account @MatthewHeimbach Chairman of the Traditionalist Worker Party. Banned in the UK. ’The fresh face of fascism.’

According to Hatewatch

Southern Indiana tradworker.org Joined January 2012 TWEETS 2,108 FOLLOW-

ING 444 FOLLOWERS 5,517 LIKES 510

15.6 Mike Enoch

@ThaRightStuff Proud American Patriot and Nationalist. The #2 Republican Party twitter account. Host of the #2 Republican Party podcast. #GOP #MAGA

United States therightstuff.biz Joined December 2012 TWEETS 6,435 FOLLOW-

ING 2,228 FOLLOWERS 20.5K LIKES 7,042

15.7 Steven Crower

Steven CrowderVerified account @scrowder http://LouderWithCrowder.com for podcasts, videos and free stuff. Love you.

Ghostlike louderwithcrowder.com Joined January 2009 TWEETS 39.6K FOLLOWING 2,856 FOLLOWERS 314K LIKES 184 LISTS 1

15.8 Andrew Anglin

https://www.splcenter.org/fighting-hate/extremist-files/individual/ andrew-anglin Andrew Anglin is the founder of the neo-Nazi Daily Stormer website, which aptly takes its name from the gutter Nazi propaganda sheet known as Der Strmer. True to that vintage, Anglin is infamous for the crudity of his language and his thinking, a contrast to his sophistication as a prolific Internet troll and serial harasser. Twitter Account Andrew Anglin @totalfascism Top antisemite and pro-Hitler activist.

Chicago, IL dailystormer.com Joined June 2013 TWEETS 93 FOLLOWING 37

FOLLOWERS 156 LIKES 1

16 Anti-Immigrant

16.1 David Horowitz

https://www.splcenter.org/fighting-hate/extremist-files/individual/ david-horowitz Andrew Anglin is the founder of the neo-Nazi Daily Stormer website, which aptly takes its name from the gutter Nazi propaganda sheet known as Der Strmer. True to that vintage, Anglin is infamous for the crudity of his language and his thinking, a contrast to his sophistication as a prolific Internet troll and serial harasser. Twitter Account David Horowitz @horowitz39 Los Angeles, Ca horowitzfreedomcenter.org Joined September 2010 David Horowitz David Horowitz @horowitz39 TWEETS 3,671 FOLLOWING 499 FOLLOWERS 19.8K LIKES 2

17 Anti LGBT

17.1 Lou Engle

https://www.splcenter.org/fighting-hate/extremist-files/individual/ lou-engle In recent years, thanks largely to his leadership of TheCall Ministries, Lou Engle has become one of the more prominent players on the American religious right. Twitter Account Lou Engle @LouEngle Lou Engle is a revivalist, visionary, and cofounder of TheCall solemn assemblies. @TheCall

United States thecall.com Joined August 2009 TWEETS 2,693 FOLLOWING 292

FOLLOWERS 56K LIKES 344

References

Michael Conover, Jacob Ratkiewicz, Matthew R Francisco, Bruno Gonc¸alves, Filippo Menczer, and Alessandro Flammini. Political polarization on twitter. *ICWSM*, 133:89–96, 2011.

Jose Alexandre Felizola Diniz-Filho, Carlos Eduardo Ramos de Sant’Ana, and Luis Mauricio Bini. An eigenvector method for estimating phylogenetic inertia. *Evolution*, pages 1247–1262, 1998.

Frank Lin and William W Cohen. Power iteration clustering. In *Proceedings of the 27th international conference on machine learning (ICML-10)*, pages 655–662, 2010.

Grzegorz Malewicz, Matthew H Austern, Aart JC Bik, James C Dehnert, Ilan Horn, Naty Leiser, and Grzegorz Czajkowski. Pregel: a system for large-scale graph processing. In *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*, pages 135–146. ACM, 2010.

Weizhong Yan, Umang Brahmakshatriya, Ya Xue, Mark Gilder, and Bowden Wise. p-pic: Parallel power iteration clustering for big data. *Journal of Parallel and Distributed computing*, 73(3):352–359, 2013.

Appendix B

Streaming API program

SteamingAllThreeGroups(Scala)
Import Notebook

Streaming All Groups

2016, Raazesh Sainudiin and Rania Sahioun

This is part of *Project MEP: Meme Evolution Programme* and supported by databricks academic partners program.

The analysis is available in the following databricks notebook: http://lamastex.org/lmse/mep/src/extendedTwitterUtils.html


```
StreamingContext.getActive.foreach{ _.stop(stopSparkContext = false) } // this will make sure all streaming job in the cluster are stopped - raaz
```

```
<console>:32: error: not found: value StreamingContext StreamingContext.getActive.foreach{ _.stop(stopSparkContext = false) } // this will make sure all streaming job in the cluster are stopped - raaz ^
```

```
%run "scalable-data-science/meme-evolution/db/src2run/extendedTwitterUtils2run"
```

Let us stream in data now

```
import org.apache.spark._
import org.apache.spark.storage._
import org.apache.spark.streaming._
import org.apache.spark.streaming.twitter.TwitterUtils

import twitter4j.auth.OAuthAuthorization
import twitter4j.conf.ConfigurationBuilder

import com.google.gson.Gson
```

```
import org.apache.spark._ import org.apache.spark.storage._ import org.apache.spark.streaming._ import org.apache.spark.streaming.twitter.TwitterUtils import twitter4j.auth.OAuthAuthorization import twitter4j.conf.ConfigurationBuilder import com.google.gson.Gson
```

Your twitter credentials

```
//twitter credentials
val MyconsumerKey       = ""
val MyconsumerSecret    = ""
```

```
val Mytoken          = ""
val MytokenSecret      = ""


System.setProperty("twitter4j.oauth.consumerKey", MyconsumerKey)
System.setProperty("twitter4j.oauth.consumerSecret", MyconsumerSecret)
System.setProperty("twitter4j.oauth.accessToken", Mytoken)
System.setProperty("twitter4j.oauth.accessTokenSecret", MytokenSecret)

val outputDirectoryRoot = s"/mnt/$MountName/datasets/MEP/AllGroupsStreaming"
val batchInterval = 5 // minutes
val timeoutJobLength =  batchInterval * 5
<console>:42: error: not found: value MountName val outputDirectoryRoot =
    s"/mnt/$MountName/datasets/MEP/AllGroupsStreaming" ^
dbutils.fs.mount(s"s3a://$AccessKey:$EncodedSecretKey@$AwsBucketName", s"/mnt/$MountName")
res5: Boolean = true
dbutils.fs.unmount(s"/mnt/$MountName") // unmount if already mounted!!!
java.rmi.RemoteException: java.lang.IllegalArgumentException: Directory not mounted: /mnt/s3_datasets;
    nested exception is:
```

Adding the complete list

The completeList as of 7/11/2016. The new list includs all the old list + individual SPLC including @RealAlexJones New section had been added to the above notebook so it would be easy to add individual in the future

"1" had been added to the AccessKey, EncodedSecretKey and BucketName to insurance that it doesn't interfere with same information from the streaming job

```
val finalCompleteList =
    sqlContext.read.parquet(RW_baseDir1+"datasets/MEP/CompleteListOfStreamingJobUsers/").rdd.map
    (r => r(0).asInstanceOf[Long])
finalCompleteList.count()
finalCompleteList: org.apache.spark.rdd.RDD[Long] = MapPartitionsRDD[35753] at map at <console>:67 res6:
    Long = 148
//Original list from the 15/10/2016
//val completeBuffList =new ListBuffer[Long]()
/*val completeList  = List[Long](43330802L, 18956212L, 85332821L, 2913151L, 31582401L, 70319221L,
    36315753L, 736025718233042945L, 3349682675L, 189618631L, 2246898978L, 1481526582L,
    4716734311L, 4502064200L, 3106483679L, 346417825L, 322027737L, 1554897007L, 1152375114L,
    1428792374L, 3999537573L, 27522964L, 42645839L, 18163042L, 25505732L, 239843089L,
    86145717L, 168541923L, 20708260L, 100101179L, 273469546L, 260131662L, 3190206607L,
    34467455L, 1180370792L, 162869041L, 368842056L, 3094694155L, 33394729L, 1132212984L,
    160474294L, 366935179L, 23724587L, 2989079504L, 33189912L, 1038333752L, 147406561L,
    356139045L, 2984570592L, 31634233L, 768286632L, 140297916L, 349032104L, 2858594918L,
    31583101L, 760842698L, 129943834L, 346944092L, 23352383L, 2842312937L, 29565212L,
    756227808L, 121553239L, 322976025L, 2585342936L, 29406343L, 614909398L, 118829680L,
    313659726L, 22959763L, 2582229654L, 29387139L, 611683035L, 109480485L, 304725986L,
    2575758176L, 28409997L, 611300773L, 103494259L, 299580303L, 2543108298L, 28010179L,
    607152697L, 92598386L, 292220830L, 20909637L, 2509728985L, 28009853L, 588733258L,
    83695459L, 262909861L, 2401210076L, 26568999L, 587284588L, 70288354L, 245243839L,
    18750581L, 2384426755L, 26209461L, 581645959L, 67118071L, 243916139L, 2296972758L,
    25792467L, 559823431L, 64319635L, 240517888L, 2175532662L, 25770641L, 559303030L,
    60550677L, 231179492L, 18277419L, 1913682588L, 25754056L, 539548061L, 52356116L,
    204154654L, 1597501970L, 24149001, 429452117L, 43037613L, 188228410L, 18149977L,
```

```
    1538485165L, 24056982L, 428605068L, 40409545L, 181012160L, 1437035906L, 23852569L,
    406860930L, 39141559L, 174199107L, 1281726260L, 23830758L, 371019945L, 34813183L,
    166824947L, 17380167L, 4173723312L, 216776631L, 18916432L, 786655970646695937L,
    779019249264173057L, 468646961L, 25073877L, 1339835893L)
*/
//To keep for now for record keeping, please do not delete list on the 7/11/2016
//val finalCompleteList17_11_2019 = finalCompleteList.collect() //forgot and added one before the save actual
    date is 7/11/2019 when the new job run
finalCompleteList17_11_2019: Array[Long] = Array(1152375114, 260131662, 1554897007, 31582401,
    15210689, 3349682675, 273469546, 36315753, 322027737, 189618631, 4502064200, 239843089,
    2913151, 168541923, 346417825, 18163042, 1428792374, 43330802, 4716734311, 86145717,
    18956212, 20708260, 100101179, 2246898978, 42645839, 27522964, 85332821,
    736025718233042945, 3999537573, 25505732, 3190206607, 34467455, 1180370792, 162869041,
    368842056, 3094694155, 33394729, 1132212984, 160474294, 366935179, 23724587, 2989079504,
    33189912, 1038333752, 147406561, 356139045, 2984570592, 31634233, 768286632, 140297916,
    349032104, 2858594918, 31583101, 760842698, 129943834, 346944092, 23352383, 2842312937,
    29565212, 756227808, 121553239, 322976025, 2585342936, 29406343, 614909398, 118829680,
    313659726, 22959763, 2582229654, 29387139, 611683035, 109480485, 304725986, 2575758176,
    28409997, 611300773, 103494259, 299580303, 2543108298, 28010179, 607152697, 92598386,
    292220830, 20909637, 2509728985, 28009853, 588733258, 83695459, 262909861, 2401210076,
    26568999, 587284588, 70288354, 245243839, 18750581, 2384426755, 26209461, 581645959,
    67118071, 243916139, 2296972758, 25792467, 559823431, 64319635, 240517888, 2175532662,
    25770641, 559303030, 60550677, 231179492, 18277419, 1913682588, 25754056, 539548061,
    52356116, 204154654, 1597501970, 24149001, 429452117, 43037613, 188228410, 18149977,
    1538485165, 24056982, 428605068, 40409545, 181012160, 1437035906, 23852569, 406860930,
    39141559, 174199107, 1281726260, 23830758, 371019945, 34813183, 166824947, 17380167,
    4173723312, 216776631, 18916432, 786655970646695937, 779019249264173057, 468646961,
    25073877, 1339835893, 23022687)
//The final list starting from the 9/11/2019
val finalCompleteList9_11_2019 = finalCompleteList.collect()
finalCompleteList9_11_2019: Array[Long] = Array(1152375114, 260131662, 1554897007, 31582401,
    15210689, 3349682675, 273469546, 36315753, 322027737, 189618631, 4502064200, 239843089,
    2913151, 168541923, 346417825, 18163042, 1428792374, 43330802, 4716734311, 86145717,
    18956212, 20708260, 100101179, 2246898978, 42645839, 27522964, 85332821,
    736025718233042945, 3999537573, 25505732, 3190206607, 34467455, 1180370792, 162869041,
    368842056, 3094694155, 33394729, 1132212984, 160474294, 366935179, 23724587, 2989079504,
    33189912, 1038333752, 147406561, 356139045, 2984570592, 31634233, 768286632, 140297916,
    349032104, 2858594918, 31583101, 760842698, 129943834, 346944092, 23352383, 2842312937,
    29565212, 756227808, 121553239, 322976025, 2585342936, 29406343, 614909398, 118829680,
    313659726, 22959763, 2582229654, 29387139, 611683035, 109480485, 304725986, 2575758176,
    28409997, 611300773, 103494259, 299580303, 2543108298, 28010179, 607152697, 92598386,
    292220830, 20909637, 2509728985, 28009853, 588733258, 83695459, 262909861, 2401210076,
    26568999, 587284588, 70288354, 245243839, 18750581, 2384426755, 26209461, 581645959,
    67118071, 243916139, 2296972758, 25792467, 559823431, 64319635, 240517888, 2175532662,
    25770641, 559303030, 60550677, 231179492, 18277419, 1913682588, 25754056, 539548061,
    52356116, 204154654, 1597501970, 24149001, 429452117, 43037613, 188228410, 18149977,
    1538485165, 24056982, 428605068, 40409545, 181012160, 1437035906, 23852569, 406860930,
    39141559, 174199107, 1281726260, 23830758, 371019945, 34813183, 166824947, 17380167,
    4173723312, 216776631, 18916432, 786655970646695937, 779019249264173057, 468646961,
    25073877, 1339835893, 23022687, 23658557)
import org.apache.spark.sql.functions._
import org.apache.spark.sql.types._

var newContextCreated = false
var numTweetsCollected = 0L // track number of tweets collected
// This is the function that creates the SteamingContext and sets up the Spark Streaming job.
def streamFunc(): StreamingContext = {
  // Create a Spark Streaming Context.
  val ssc = new StreamingContext(sc, Minutes(batchInterval))
```

```
  // Create a Twitter Stream for the input source.
  val auth = Some(new OAuthAuthorization(new ConfigurationBuilder().build()))
  val follow = finalCompleteList9_11_2019
  val twitterStream = ExtendedTwitterUtils.createStream(ssc, auth, track, follow)
  val twitterStreamJson = twitterStream.map(x => { val gson = new Gson();
                                                   val xJson = gson.toJson(x)
                                                   xJson
                                                  })

val partitionsEachInterval = 1 // This tells the number of partitions in each RDD of tweets in the DStream.

twitterStreamJson.foreachRDD((rdd, time) => { // for each filtered RDD in the DStream
      val count = rdd.count()
      if (count > 0) {
        val outputRDD = rdd.repartition(partitionsEachInterval) // repartition as desired
        val outputDF = outputRDD.toDF("tweetAsJsonString")
        val year = (new java.text.SimpleDateFormat("yyyy")).format(new java.util.Date())
        val month = (new java.text.SimpleDateFormat("MM")).format(new java.util.Date())
        val day = (new java.text.SimpleDateFormat("dd")).format(new java.util.Date())
        val hour = (new java.text.SimpleDateFormat("HH")).format(new java.util.Date())
        dbutils.fs.mount(s"s3a://$AccessKey:$EncodedSecretKey@$AwsBucketName", s"/mnt/$MountName")
        outputDF.write.mode(SaveMode.Append).parquet(outputDirectoryRoot+ "/"+ year + "/" + month + "/" +
              day + "/" + hour + "/" + time.milliseconds)
        dbutils.fs.unmount(s"/mnt/$MountName")
        numTweetsCollected += count // update with the latest count
      }
  })
  newContextCreated = true
  ssc
}
import org.apache.spark.sql.functions._ import org.apache.spark.sql.types._ newContextCreated: Boolean =
        false numTweetsCollected: Long = 0 streamFunc: ()org.apache.spark.streaming.StreamingContext
val ssc = StreamingContext.getActiveOrCreate(streamFunc)
ssc: org.apache.spark.streaming.StreamingContext = org.apache.spark.streaming.StreamingContext@afe3c70
ssc.start()
//ssc.awaitTerminationOrTimeout(timeoutJobLength) // you only need one of these to start
// THIS IS RUNNING!!! --Job started on 15/10/2016 9:44 p.m. Ended on 7/11/2016 12:11 p.m.
// THIS IS RUNNING!!! --Job started on 07/11/2016 12:13 p.m. Ended on 9/11/2016 11:02 a.m.
// THIS IS RUNNING!!! --Job started on 09/11/2016 11:03 p.m. Ended on 18/11/2016 4:12 p.m.
// This is Running!!! --Job started on 24/11/2016 10:30
//StreamingContext.getActive.foreach { _.stop(stopSparkContext = false) } // this will make sure all streaming
        job in the cluster are stopped
```

Appendix C

Rest API program

04_TIN_02_Update_3rdUSDebate(Scala)
Import Notebook

Modifies Sampled Data in s3 R/W datasets bucket!!!
Grow the Tweet Ideological Network (TIN) from the Tweet Transmission Tree (TTT)
This is to Update the Process Only (i.e. to increase sample size) !!!
Assumed that TIN_01_Initialize_ Notebook was already used to start the process (Raaz did on Oct 28th 2016 in Chch)

```
1+1
res1: Int = 2
//import twitter4j.RateLimitStatus;

import scala.collection.mutable.ArrayBuffer
import twitter4j._
import twitter4j.conf._
import scala.collection.JavaConverters._
import org.apache.spark.sql.Row;
import org.apache.spark.sql.types.{StructType, StructField, StringType};
import twitter4j.ResponseList;
import com.google.gson.Gson
import org.apache.spark.sql.functions._
import org.apache.spark.sql.types._


//-------TWITTER
// set configurationbuilder for twitter
val cb = new ConfigurationBuilder()

val twitter = {
  val c = new ConfigurationBuilder
    c.setDebugEnabled(true)
    .setOAuthConsumerKey(consumerKey)
    .setOAuthConsumerSecret(consumerSecret)
    .setOAuthAccessToken(token)
    .setOAuthAccessTokenSecret(tokenSecret);

  new TwitterFactory(c.build()).getInstance()
}
//---------- end of TWITTER
```

The data needed to obtain the TTT in order to grow its TIN

Decide whether you are going to write to s3 or locally to dbfs -- **ONLY s3 is tested / supported**

Getting the Tweet-Transmission-Tree (TTT) DataFrame for 20161019

We will first get the retweets of Trump and Clinton from:
verified accounts and
incrmentally from increasing the randomly sampled fraction with the same Seed 123456789L
then obtaining their user-timelines of latest 200 tweet status objects and
finally filtering for retweets from the tweet status objects in the user-time-lines to build their TIN based on - in another notebook **TIN_03_**

```
val groupTTTDF = sqlContext.read.parquet(baseDir+"datasets/MEP/AllGroupsStreaming/20161019groupTTTDF")
// some filtering criteria
val minimumAgeSinceAccountCreatedInDays=100
val userTimeLineDirName = baseDir+"datasets/MEP/userTimeLine/" // dir to store the user-timeline tweets of the retweeters of Trump and Clinton
```

```
groupTTTDF: org.apache.spark.sql.DataFrame = [CurrentTweetDate: timestamp, CurrentTwID: bigint, CreationDateOfOrgTwInRT: timestamp, OriginalTwIDinRT: bigint, CreationDateOfOrgTwInQT: timestamp, OriginalTwIDinQT: bigint, OriginalTwIDinReply: bigint, CPostUserId: bigint, userCreatedAtDate: timestamp, OPostUserIdinRT: bigint, OPostUserIdinQT: bigint, CPostUserName: string, OPostUserNameinRT: string, OPostUserNameinQT: string, CPostUserSN: string, OPostUserSNinRT: string, OPostUserSNinQT: string, favouritesCount: bigint, followersCount: bigint, friendsCount: bigint, isVerified: boolean, isGeoEnabled: boolean, CurrentTweet: string, UMentionRTiD: array<bigint>, UMentionRTsN: array<string>, UMentionQTiD: array<bigint>, UMentionQTsN: array<string>, UMentionASiD: array<bigint>, UMentionASsN: array<string>, TweetType: string, MentionType: string, Weight: bigint] minimumAgeSinceAccountCreatedInDays: Int = 100 userTimeLineDirName: String = /mnt/s3_ReadWrite/datasets/MEP/userTimeLine/
```

Verified Tweets were already sampled in TIN_01_Initialize_ notebook

We need to take it to make a Union with the latest sample we will update below.

```
val TrumpClintonRetweetsVerified = groupTTTDF
  .filter($"isVerified"===true)
  .filter($"tweetType"==="ReTweet")
  .withColumn("now", lit(current_timestamp()))

        .withColumn("daysSinceUserCreated",datediff($"now",$"userCreatedAtDate"))
                .drop($"now")

        .filter($"daysSinceUserCreated">minimumAgeSinceAccountCreatedInDays)
  .filter($"OPostUserSNinRT"==="realDonaldTrump" ||
        $"OPostUserSNinRT"==="HillaryClinton")
  .filter($"followersCount">2 && $"friendsCount">2)// filtering accounts with <3 friends or followers
  .cache()

display(TrumpClintonRetweetsVerified)
```

```
TrumpClintonRetweetsVerified.count()
res6: Long = 294
```

Sample More and accure in s3 - this is where we keep resampling!!!

Now let us go after the non-verified but Geo-enalbled retweeters - a small sample of them, say

```
val TrumpClintonRetweetsUnVerifiedGeoEnabled = groupTTTDF
  .filter($"isVerified"===false && $"isGeoEnabled"===true)
  .filter($"tweetType"==="ReTweet")
  .withColumn("now", lit(current_timestamp()))

      .withColumn("daysSinceUserCreated",datediff($"now",$"userCreatedAtDate"))
                  .drop($"now")

      .filter($"daysSinceUserCreated">minimumAgeSinceAccountCreatedInDays)
  .filter($"OPostUserSNinRT"==="realDonaldTrump" ||
      $"OPostUserSNinRT"==="HillaryClinton")
  .filter($"followersCount">2 && $"friendsCount">2)// filtering accounts with <3 friends or
      followers
  .cache()

display(TrumpClintonRetweetsUnVerifiedGeoEnabled)
Showing the first 1000 rows.
val TrumpClintonRetweetsUnVerifiedGeoEnabledSample =
      TrumpClintonRetweetsUnVerifiedGeoEnabled.sample(false,0.006,123456789L) //
      our HARD seed = 123456789L DONT CHANGE THIS!!!
TrumpClintonRetweetsUnVerifiedGeoEnabledSample: org.apache.spark.sql.DataFrame =
      [CurrentTweetDate: timestamp, CurrentTwID: bigint, CreationDateOfOrgTwInRT:
      timestamp, OriginalTwIDinRT: bigint, CreationDateOfOrgTwInQT: timestamp,
      OriginalTwIDinQT: bigint, OriginalTwIDinReply: bigint, CPostUserId: bigint,
      userCreatedAtDate: timestamp, OPostUserIdinRT: bigint, OPostUserIdinQT: bigint,
      CPostUserName: string, OPostUserNameinRT: string, OPostUserNameinQT: string,
      CPostUserSN: string, OPostUserSNinRT: string, OPostUserSNinQT: string,
      favouritesCount: bigint, followersCount: bigint, friendsCount: bigint, isVerified:
      boolean, isGeoEnabled: boolean, CurrentTweet: string, UMentionRTiD:
      array<bigint>, UMentionRTsN: array<string>, UMentionQTiD: array<bigint>,
      UMentionQTsN: array<string>, UMentionASiD: array<bigint>, UMentionASsN:
      array<string>, TweetType: string, MentionType: string, Weight: bigint,
      daysSinceUserCreated: int]
val allRetweeters2Sample =
      TrumpClintonRetweetsUnVerifiedGeoEnabledSample.select($"CPostUserID".alias("
      userID")).distinct().cache()
allRetweeters2Sample.count()
allRetweeters2Sample: org.apache.spark.sql.DataFrame = [userID: bigint] res32: Long = 350
var usersTimeLinedSoFar =
      sqlContext.read.parquet(baseDir+"datasets/MEP/usersTimeLinedSoFar") // for
      subsequent iterations
usersTimeLinedSoFar.count() // number of users who have been "time-lined", i.e. up to 200
      most recent tweets have been collected from their user-timelines
```

```
usersTimeLinedSoFar: org.apache.spark.sql.DataFrame = [userId: bigint] res33: Long = 551
// if the count is zero then increase the second argument to
        TrumpClintonRetweetsUnVerifiedGeoEnabled.sample three cells above
val allRetweeters2ActuallySample = allRetweeters2Sample.except(usersTimeLinedSoFar)
allRetweeters2ActuallySample.count() // number of new users we need to time-line
allRetweeters2ActuallySample: org.apache.spark.sql.DataFrame = [userID: bigint] res34:
        Long = 0
```

Make sure allRetweeters2ActuallySample is not bigger than 200-300 at least in CE

```
val allRetweeters2ActuallySampleArray =
        allRetweeters2ActuallySample.map(t=>t.getAs[Long](0)).collect()

def getUserTimeLine (userId : Long)={
  try {
      val page = new Paging(1, 200);
      val tweetsOfUserId = sc.parallelize(twitter.getUserTimeline(userId, page).asScala)
      val userIdAndStatusJsonString = tweetsOfUserId.map(x => { val gson = new Gson();
                                              val toJson= gson.toJson(x);
                                              (userId , toJson)
                                             }
                                        ).toDF("userId", "statusJsonString")
     userIdAndStatusJsonString.write.mode(SaveMode.Append).parquet(
        userTimeLineDirName + userId.toString())
   } catch {
         case e: TwitterException =>{
              if (e.getErrorCode()== 429){
                Thread.sleep(60*15 + 5)
              } else if ((e.getErrorCode() == 500) || (e.getErrorCode() == 502) ||
        (e.getErrorCode() == 503) ||(e.getErrorCode() == 504)){
                 Thread.sleep(1000)
          }
        }
      }
 }

// let's write what we are going to collect next
sc.parallelize(allRetweeters2ActuallySampleArray)
  .toDF("userId")
  .write.mode(SaveMode.Overwrite).parquet(baseDir+"datasets/MEP/usersTimeLinedToBe")

allRetweeters2ActuallySampleArray.foreach(t => {
   getUserTimeLine (t)
})

getUserTimeLine: (userId: Long)Unit
//let's read back what we were going to collect
val usersJustTimeLined =
        sqlContext.read.parquet(baseDir+"datasets/MEP/usersTimeLinedToBe").cache()
```

```
usersJustTimeLined.count()
var usersTimeLinedSoFar =
    sqlContext.read.parquet(baseDir+"datasets/MEP/usersTimeLinedSoFar").cache()
usersTimeLinedSoFar.count()
val usersTimeLinedSoFarUpdated = usersTimeLinedSoFar.unionAll(usersJustTimeLined)
usersTimeLinedSoFarUpdated.write.mode(SaveMode.Overwrite).parquet(baseDir+"datasets/
    MEP/usersTimeLinedSoFar")
//remove the pending job
dbutils.fs.rm(baseDir+"datasets/MEP/usersTimeLinedToBe",true)
usersJustTimeLined.unpersist()
usersTimeLinedSoFar.unpersist()
//re-read and count total
usersTimeLinedSoFar =
    sqlContext.read.parquet(baseDir+"datasets/MEP/usersTimeLinedSoFar")
usersTimeLinedSoFar.count()
```

```
usersJustTimeLined: org.apache.spark.sql.DataFrame = [userId: bigint]
    usersTimeLinedSoFar: org.apache.spark.sql.DataFrame = [userId: bigint]
    usersTimeLinedSoFarUpdated: org.apache.spark.sql.DataFrame = [userId: bigint]
    usersTimeLinedSoFar: org.apache.spark.sql.DataFrame = [userId: bigint] res31: Long
    = 551
```

```
display(dbutils.fs.ls(baseDir+"datasets/MEP/"))
```

dbfs:/mnt/s3_ReadWrite/datasets/MEP/AllGroupsStreaming/
dbfs:/mnt/s3_ReadWrite/datasets/MEP/SPLC/
dbfs:/mnt/s3_ReadWrite/datasets/MEP/SPLC20161206/
dbfs:/mnt/s3_ReadWrite/datasets/MEP/TrumpClinton20161006/
dbfs:/mnt/s3_ReadWrite/datasets/MEP/userTimeLine/
dbfs:/mnt/s3_ReadWrite/datasets/MEP/usersTimeLinedSoFar/
path

Now write down the sampled TTT of Trump-Clinton Retweets

```
val currentFullSampleOfTrumpClintonRetweets =
    TrumpClintonRetweetsUnVerifiedGeoEnabledSample.unionAll(TrumpClintonRetwe
    etsVerified)
```

```
currentFullSampleOfTrumpClintonRetweets: org.apache.spark.sql.DataFrame =
    [CurrentTweetDate: timestamp, CurrentTwID: bigint, CreationDateOfOrgTwInRT:
    timestamp, OriginalTwIDinRT: bigint, CreationDateOfOrgTwInQT: timestamp,
    OriginalTwIDinQT: bigint, OriginalTwIDinReply: bigint, CPostUserId: bigint,
    userCreatedAtDate: timestamp, OPostUserIdinRT: bigint, OPostUserIdinQT: bigint,
    CPostUserName: string, OPostUserNameinRT: string, OPostUserNameinQT: string,
    CPostUserSN: string, OPostUserSNinRT: string, OPostUserSNinQT: string,
    favouritesCount: bigint, followersCount: bigint, friendsCount: bigint, isVerified:
    boolean, isGeoEnabled: boolean, CurrentTweet: string, UMentionRTiD:
    array<bigint>, UMentionRTsN: array<string>, UMentionQTiD: array<bigint>,
    UMentionQTsN: array<string>, UMentionASiD: array<bigint>, UMentionASsN:
```

```
array<string>, TweetType: string, MentionType: string, Weight: bigint, daysSinceUserCreated: int]
currentFullSampleOfTrumpClintonRetweets.count
res36: Long = 652
display(currentFullSampleOfTrumpClintonRetweets)
currentFullSampleOfTrumpClintonRetweets.write.mode(SaveMode.Overwrite).parquet(baseDir+"datasets/MEP/AllGroupsStreaming/20161019CurrentlySampledTrumpClintonTTTDF")
```

Takes a long time and not necessary if the jobs finish as expected

Some checking of output - but this should be done in TIN_3rdUSDebate_03Build notebook

```
val retweeters200TweetsRaw = sqlContext.read.parquet(baseDir+"datasets/MEP/userTimeLine/*")
val retweeters200Tweets = sqlContext.read.json(retweeters200TweetsRaw.map({case Row(val0: Long, val1: String) => val1}))
retweeters200Tweets.cache()
retweeters200Tweets.count()
```


```
retweeters200TweetsRaw: org.apache.spark.sql.DataFrame = [userId: bigint, statusJsonString: string] retweeters200Tweets: org.apache.spark.sql.DataFrame = [contributorsIDs: array<string>, createdAt: string, currentUserRetweetId: bigint, extendedMediaEntities: array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,type:string,url:string,videoAspectRatioHeight:bigint,videoAspectRatioWidth:bigint,videoDurationMillis:bigint,videoVariants:array<struct<bitrate:bigint,contentType:string,url:string>>>>, favoriteCount: bigint, geoLocation: struct<latitude:double,longitude:double>, hashtagEntities: array<struct<end:bigint,start:bigint,text:string>>, id: bigint, inReplyToScreenName: string, inReplyToStatusId: bigint, inReplyToUserId: bigint, isFavorited: boolean, isPossiblySensitive: boolean, isRetweeted: boolean, isTruncated: boolean, lang: string, mediaEntities: array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,type:string,url:string>>, place: struct<boundingBoxCoordinates:array<array<struct<latitude:double,longitude:double>>>,boundingBoxType:string,containedWithIn:array<string>,country:string,countryCode:string,fullName:string,id:string,name:string,placeType:string,url:string>, quotedStatus: struct<contributorsIDs:array<string>,createdAt:string,currentUserRetweetId:bigint,extendedMediaEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,type:string,url:string,videoAspectRatioHeight:bigint,videoAspectRatioWidth:bigint,videoDurationMillis:bigint,videoVariants:array<struct<bitrate:bigint,con
```

tentType:string,url:string>>>>,favoriteCount:bigint,geoLocation:struct<latitude:double,longitude:double>,hashtagEntities:array<struct<end:bigint,start:bigint,text:string>>,id:bigint,inReplyToScreenName:string,inReplyToStatusId:bigint,inReplyToUserId:bigint,isFavorited:boolean,isPossiblySensitive:boolean,isRetweeted:boolean,isTruncated:boolean,lang:string,mediaEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,type:string,url:string>>,place:struct<boundingBoxCoordinates:array<array<struct<latitude:double,longitude:double>>>,boundingBoxType:string,containedWithIn:array<string>,country:string,countryCode:string,fullName:string,id:string,name:string,placeType:string,url:string>,quotedStatusId:bigint,retweetCount:bigint,source:string,symbolEntities:array<struct<end:bigint,start:bigint,text:string>>,text:string,urlEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>>,user:struct<createdAt:string,description:string,descriptionURLEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>>,favouritesCount:bigint,followersCount:bigint,friendsCount:bigint,id:bigint,isContributorsEnabled:boolean,isDefaultProfile:boolean,isDefaultProfileImage:boolean,isFollowRequestSent:boolean,isGeoEnabled:boolean,isProtected:boolean,isVerified:boolean,lang:string,listedCount:bigint,location:string,name:string,profileBackgroundColor:string,profileBackgroundImageUrl:string,profileBackgroundImageUrlHttps:string,profileBackgroundTiled:boolean,profileBannerImageUrl:string,profileImageUrl:string,profileImageUrlHttps:string,profileLinkColor:string,profileSidebarBorderColor:string,profileSidebarFillColor:string,profileTextColor:string,profileUseBackgroundImage:boolean,screenName:string,showAllInlineMedia:boolean,statusesCount:bigint,timeZone:string,translator:boolean,url:string,urlEntity:struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>,utcOffset:bigint>,userMentionEntities:array<struct<end:bigint,id:bigint,name:string,screenName:string,start:bigint>>>,
quotedStatusId: bigint, retweetCount: bigint, retweetedStatus:
struct<contributorsIDs:array<string>,createdAt:string,currentUserRetweetId:bigint,extendedMediaEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,type:string,url:string,videoAspectRatioHeight:bigint,videoAspectRatioWidth:bigint,videoDurationMillis:bigint,videoVariants:array<struct<bitrate:bigint,contentType:string,url:string>>>>,favoriteCount:bigint,geoLocation:struct<latitude:double,longitude:double>,hashtagEntities:array<struct<end:bigint,start:bigint,text:string>>,id:bigint,inReplyToScreenName:string,inReplyToStatusId:bigint,inReplyToUserId:bigint,isFavorited:boolean,isPossiblySensitive:boolean,isRetweeted:boolean,isTruncated:boolean,lang:string,mediaEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,type:string,url:string>>,place:struct<boundingBoxCoordinates:array<array<struct<latitude:double,longitude:double>>>,boundingBoxType:string,containedWithIn:array<string>,country:string,countryCode:string,fullName:string,id:string,name:string,placeType:string,url:string>,quotedStatus:struct<contributorsIDs:array<string>,createdAt:string,currentUserRetweetId:bigint,extendedMediaEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,id:bigint,mediaUR

L:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,resize:bigint,width:
bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<height:bigint,resize:
bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>>,start:bigint,typ
e:string,url:string,videoAspectRatioHeight:bigint,videoAspectRatioWidth:bigint,vide
oDurationMillis:bigint,videoVariants:array<struct<bitrate:bigint,contentType:string,u
rl:string>>>>,favoriteCount:bigint,geoLocation:struct<latitude:double,longitude:doub
le>,hashtagEntities:array<struct<end:bigint,start:bigint,text:string>>,id:bigint,inReply
ToScreenName:string,inReplyToStatusId:bigint,inReplyToUserId:bigint,isFavorited:b
oolean,isPossiblySensitive:boolean,isRetweeted:boolean,isTruncated:boolean,lang:stri
ng,mediaEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,id:
bigint,mediaURL:string,mediaURLHttps:string,sizes:struct<0:struct<height:bigint,res
ize:bigint,width:bigint>,1:struct<height:bigint,resize:bigint,width:bigint>,2:struct<hei
ght:bigint,resize:bigint,width:bigint>,3:struct<height:bigint,resize:bigint,width:bigint>
>,start:bigint,type:string,url:string>>,place:struct<boundingBoxCoordinates:array<arr
ay<struct<latitude:double,longitude:double>>>,boundingBoxType:string,containedW
ithIn:array<string>,country:string,countryCode:string,fullName:string,id:string,name:
string,placeType:string,url:string>,quotedStatusId:bigint,retweetCount:bigint,source:s
tring,symbolEntities:array<struct<end:bigint,start:bigint,text:string>>,text:string,urlE
ntities:array<struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url
:string>>,user:struct<createdAt:string,description:string,descriptionURLEntities:array
<struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>>,fa
vouritesCount:bigint,followersCount:bigint,friendsCount:bigint,id:bigint,isContributo
rsEnabled:boolean,isDefaultProfile:boolean,isDefaultProfileImage:boolean,isFollowR
equestSent:boolean,isGeoEnabled:boolean,isProtected:boolean,isVerified:boolean,lan
g:string,listedCount:bigint,location:string,name:string,profileBackgroundColor:string,
profileBackgroundImageUrl:string,profileBackgroundImageUrlHttps:string,profileBa
ckgroundTiled:boolean,profileBannerImageUrl:string,profileImageUrl:string,profileI
mageUrlHttps:string,profileLinkColor:string,profileSidebarBorderColor:string,profile
SidebarFillColor:string,profileTextColor:string,profileUseBackgroundImage:boolean,
screenName:string,showAllInlineMedia:boolean,statusesCount:bigint,timeZone:string
,translator:boolean,url:string,urlEntity:struct<displayURL:string,end:bigint,expanded
URL:string,start:bigint,url:string>,utcOffset:bigint,withheldInCountries:array<string>
>,userMentionEntities:array<struct<end:bigint,id:bigint,name:string,screenName:strin
g,start:bigint>>,withheldInCountries:array<string>>,quotedStatusId:bigint,retweetCo
unt:bigint,scopes:struct<placeIds:array<string>>,source:string,symbolEntities:array<s
truct<end:bigint,start:bigint,text:string>>,text:string,urlEntities:array<struct<displayU
RL:string,end:bigint,expandedURL:string,start:bigint,url:string>>,user:struct<created
At:string,description:string,descriptionURLEntities:array<struct<displayURL:string,e
nd:bigint,expandedURL:string,start:bigint,url:string>>,favouritesCount:bigint,followe
rsCount:bigint,friendsCount:bigint,id:bigint,isContributorsEnabled:boolean,isDefault
Profile:boolean,isDefaultProfileImage:boolean,isFollowRequestSent:boolean,isGeoE
nabled:boolean,isProtected:boolean,isVerified:boolean,lang:string,listedCount:bigint,l
ocation:string,name:string,profileBackgroundColor:string,profileBackgroundImageUr
l:string,profileBackgroundImageUrlHttps:string,profileBackgroundTiled:boolean,prof
ileBannerImageUrl:string,profileImageUrl:string,profileImageUrlHttps:string,profileL
inkColor:string,profileSidebarBorderColor:string,profileSidebarFillColor:string,profil
eTextColor:string,profileUseBackgroundImage:boolean,screenName:string,showAllI
nlineMedia:boolean,statusesCount:bigint,timeZone:string,translator:boolean,url:string
,urlEntity:struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:str
ing>,utcOffset:bigint,withheldInCountries:array<string>>,userMentionEntities:array<

```
struct<end:bigint,id:bigint,name:string,screenName:string,start:bigint>>,withheldInCountries:array<string>>, source: string, symbolEntities: array<struct<end:bigint,start:bigint,text:string>>, text: string, urlEntities: array<struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>>, user: struct<createdAt:string,description:string,descriptionURLEntities:array<struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>>,favouritesCount:bigint,followersCount:bigint,friendsCount:bigint,id:bigint,isContributorsEnabled:boolean,isDefaultProfile:boolean,isDefaultProfileImage:boolean,isFollowRequestSent:boolean,isGeoEnabled:boolean,isProtected:boolean,isVerified:boolean,lang:string,listedCount:bigint,location:string,name:string,profileBackgroundColor:string,profileBackgroundImageUrl:string,profileBackgroundImageUrlHttps:string,profileBackgroundTiled:boolean,profileBannerImageUrl:string,profileImageUrl:string,profileImageUrlHttps:string,profileLinkColor:string,profileSidebarBorderColor:string,profileSidebarFillColor:string,profileTextColor:string,profileUseBackgroundImage:boolean,screenName:string,showAllInlineMedia:boolean,statusesCount:bigint,timeZone:string,translator:boolean,url:string,urlEntity:struct<displayURL:string,end:bigint,expandedURL:string,start:bigint,url:string>,utcOffset:bigint>, userMentionEntities: array<struct<end:bigint,id:bigint,name:string,screenName:string,start:bigint>>, withheldInCountries: array<string>] res17: Long = 95241
```

```
val retweetersTimeLinedSoFar = retweeters200Tweets.select($"user.Id").distinct().cache()
retweetersTimeLinedSoFar.count()
```

```
retweetersTimeLinedSoFar: org.apache.spark.sql.DataFrame = [Id: bigint] res18: Long = 481
```

The number of distinct retweetersTimeLinedSoFar should equal the number of usersTimeLinedSoFar. So do it one small batch at a time...

Make sure you unmount when done!

```
if (write2s3) { // make sure you unmount when done!!!
  //dbutils.fs.unmount("/mnt/s3_ReadWrite"); // hard-coded
  dbutils.fs.unmount(s"/mnt/$MountName");
}
```

```
/mnt/s3_ReadWrite has been unmounted. res39: AnyVal = true
```

Appendix D

Results list

Results_configModelTesting(Scala)

Import Notebook

Configuration Model testing for splc paper

```
//imports
import org.apache.spark.sql.types.{StructType, StructField, StringType};
import org.apache.spark.sql.functions._
import org.apache.spark.sql.DataFrame

import sqlContext.implicits
import org.apache.spark.mllib.rdd.RDDFunctions._
```

import org.apache.spark.sql.types.{StructType, StructField, StringType} import org.apache.spark.sql.functions._ import org.apache.spark.sql.DataFrame import sqlContext.implicits import org.apache.spark.mllib.rdd.RDDFunctions._

```
val allRetweets2016SrcIdDstId =
sqlContext.read.parquet("/datasets/MEP/AllGroupsStreaming/allRetweets2016SrcIdDstIdDF").cache()
allRetweets2016SrcIdDstId.count()
```

allRetweets2016SrcIdDstId: org.apache.spark.sql.DataFrame = [OPostUserIDinRT: bigint, CPostUserID: bigint] res0: Long = 12984331

```
allRetweets2016SrcIdDstId.count()
```

res1: Long = 12984331

```
allRetweets2016SrcIdDstId.distinct.count
```

res2: Long = 4412891

```
allRetweets2016SrcIdDstId.select("OPostUserIDinRT").unionAll(allRetweets2016SrcIdDstId.select("CPostUserID")).distinct.count()
```

res3: Long = 2451081

```
val politicalAccountsDF=sc.parallelize(Seq((216776631L,"BernieSanders"),
(18916432L,"SpeakerRyan"),
//(468646961L,"TomiLahren"),
(25073877L,"realDonaldTrump"),
(1339835893L,"HillaryClinton"),
(23022687L,"tedcruz"))).toDF("id","PoliticalScreenName")
//display(politicalAccountsDF)

val stdSplc = sqlContext.read.parquet("datasets/MEP/CompleteListOfSPLC/stdSplc")
val stdSplcLeaderIDAndIdeology = stdSplc.select($"LeaderIDLong",$"Ideology")
```

politicalAccountsDF: org.apache.spark.sql.DataFrame = [id: bigint, PoliticalScreenName: string] stdSplc: org.apache.spark.sql.DataFrame = [Ideology: string, LeaderIDLong: bigint, ScreenName: string, FollowerCount: int] stdSplcLeaderIDAndIdeology: org.apache.spark.sql.DataFrame = [LeaderIDLong: bigint, Ideology: string]

```
display(allRetweets2016SrcIdDstId.join(politicalAccountsDF,allRetweets2016SrcIdDstId("CPostUserID")===politicalAccountsDF("id")).drop("id").withColumn("count",lit(1.0)).groupBy("PoliticalScreenName").agg(sum("count").as("RTsOfOthersCount")).orderBy($"RTsOfOthersCount".desc)
```

```
.join(allRetweets2016SrcIdDstId.join(politicalAccountsDF,allRetweets2016SrcIdDstId("CPostUserID")===politicalAccountsDF("id")).drop("id").distinct().withColumn("count",lit(1.0)).groupBy("PoliticalScreenName").agg(sum("count").as("RTrsOfOthersCount")).orderBy($"RTrsOfOthersCount".desc),"PoliticalScreenName")

        .join(allRetweets2016SrcIdDstId.join(politicalAccountsDF,allRetweets2016SrcIdDstId("OPostUserIDinRT")===politicalAccountsDF("id")).drop("id").withColumn("count",lit(1.0)).groupBy("PoliticalScreenName").agg(sum("count").as("RTsCount")).orderBy($"RTsCount".desc)
.join(allRetweets2016SrcIdDstId.join(politicalAccountsDF,allRetweets2016SrcIdDstId("OPostUserIDinRT")===politicalAccountsDF("id")).drop("id").distinct().withColumn("count",lit(1.0)).groupBy("PoliticalScreenName").agg(sum("count").as("RTrsCount")).orderBy($"RTrsCount".desc),"PoliticalScreenName"),"PoliticalScreenName")
)
```

PoliticalScreenName	RTsOfOthersCount
realDonaldTrump	40
tedcruz	322
SpeakerRyan	769
BernieSanders	107
HillaryClinton	225

```
def cutAndReWiresrcIdDstIdRetweetsDFAtRandom(inputDF: DataFrame, srcColName: String, dstColName: String): DataFrame = {
  val indexedInputDF = inputDF.rdd.map{ case Row(s: Long, d: Long) => (s, d) }
                    .zipWithIndex.map(tuple => (tuple._1._1, tuple._1._2, tuple._2))
                    .toDF(srcColName,dstColName,"ID")
  indexedInputDF.select(srcColName,"ID")
         .join(indexedInputDF.withColumn("rand", rand()).orderBy($"rand").drop($"rand")
                .select(dstColName).rdd.map{ case Row(d: Long) => d
      }.zipWithIndex.toDF(dstColName,"ID"),
           "ID")
         .drop("ID")
}

def cutAndReWiresrcIdDstIdRetweetsIndexedDFAtRandom(indexedInputDF: DataFrame, srcColName: String, dstColName: String, IDColName: String): DataFrame = {
  indexedInputDF.select(srcColName,IDColName)
         .join(indexedInputDF.withColumn("rand", rand()).orderBy($"rand").drop($"rand")
                .select(dstColName).rdd.map{ case Row(d: Long) => d
      }.zipWithIndex.toDF(dstColName,IDColName),
           IDColName)
         .drop(IDColName)
}

def crossWiresrcIdDstIdRetweetsDFAtRandom(inputDF: DataFrame, srcColname: String, dstColName: String): DataFrame = {
  val randInputDF = inputDF.withColumn("rand", rand()).orderBy($"rand").drop($"rand")
  randInputDF.rdd
     .map{ case Row(x: Long, y: Long) => (x, y) }
     .sliding(2,2)
     .flatMap { case Array((x1, y1), (x2, y2)) => Array((x1, y2), (x2, y1)) }
     .toDF(srcColname,dstColName)
```

```
}

def srcIdDstIdRetweetsDFToRetweetWeightedDF(inputDF: DataFrame, srcColname: String, dstColName:
        String): DataFrame = {
    inputDF.withColumn("Weight",lit(1.0))
        .groupBy(srcColname,dstColName).agg(sum("Weight").alias("RTWeight"))
    }

def srcIdDstIdSrcClusterRetweetsDFToRetweetWeightedDF(inputDF: DataFrame, srcColName: String,
        dstColName: String, srcClusterColName: String): DataFrame = {
    inputDF.withColumn("Weight",lit(1.0))
        .groupBy(srcColName,dstColName,srcClusterColName).agg(sum("Weight").alias("RTWeight"))
    }

def srcIdDstIdSrcClusterRetweetsDFToRetweetWeightedDFWithInAndOutRetweetDegree(inputDF:
        DataFrame, srcColName: String, dstColName: String, srcClusterColName: String, RetweetThreshold:
        Double): DataFrame = {
    val a = srcIdDstIdSrcClusterRetweetsDFToRetweetWeightedDF(inputDF, srcColName, dstColName,
        srcClusterColName).filter($"RTWeight">RetweetThreshold)
    val outRTDegree = a.groupBy(srcColName).agg(sum("RTWeight").alias("OutRTWeight"))
    val inRTDegree  = a.groupBy(dstColName).agg(sum("RTWeight").alias("InRTWeight"))
    a.join(inRTDegree,dstColName).join(outRTDegree,srcColName)
}

// need a cross-wiring function that will take srcId, dstId, srcCluster, OutRTWeight, InRTWeight and
        OutRTWeight
def crossWiresrcIdDstIdSrcClusterRetweetsDFAtRandom(inputDF: DataFrame, srcColName: String,
        dstColName: String, srcClusterColName: String): DataFrame = {
    val randInputDF = inputDF.withColumn("rand", rand()).orderBy($"rand").drop($"rand")
    randInputDF.rdd
        .map{ case Row(x: Long, y: Long, s: Integer) => (x, y, s) }
        .sliding(2,2)
        .flatMap { case Array((x1, y1, s1), (x2, y2, s2)) => Array((x1, y2, s1), (x2, y1, s2)) }
        .toDF(srcColName,dstColName,srcClusterColName)
}

cutAndReWiresrcIdDstIdRetweetsDFAtRandom: (inputDF: org.apache.spark.sql.DataFrame, srcColName:
        String, dstColName: String)org.apache.spark.sql.DataFrame
        cutAndReWiresrcIdDstIdRetweetsIndexedDFAtRandom: (indexedInputDF:
        org.apache.spark.sql.DataFrame, srcColName: String, dstColName: String, IDColName:
        String)org.apache.spark.sql.DataFrame crossWiresrcIdDstIdRetweetsDFAtRandom: (inputDF:
        org.apache.spark.sql.DataFrame, srcColname: String, dstColName:
        String)org.apache.spark.sql.DataFrame srcIdDstIdRetweetsDFToRetweetWeightedDF: (inputDF:
        org.apache.spark.sql.DataFrame, srcColname: String, dstColName:
        String)org.apache.spark.sql.DataFrame srcIdDstIdSrcClusterRetweetsDFToRetweetWeightedDF:
        (inputDF: org.apache.spark.sql.DataFrame, srcColName: String, dstColName: String,
        srcClusterColName: String)org.apache.spark.sql.DataFrame
        srcIdDstIdSrcClusterRetweetsDFToRetweetWeightedDFWithInAndOutRetweetDegree: (inputDF:
        org.apache.spark.sql.DataFrame, srcColName: String, dstColName: String, srcClusterColName: String,
        RetweetThreshold: Double)org.apache.spark.sql.DataFrame
        crossWiresrcIdDstIdSrcClusterRetweetsDFAtRandom: (inputDF: org.apache.spark.sql.DataFrame,
        srcColName: String, dstColName: String, srcClusterColName: String)org.apache.spark.sql.DataFrame
stdSplc
.show(55)
+------------------+------------------+----------------+-------------+ | Ideology| LeaderIDLong|
        ScreenName|FollowerCount| +------------------+------------------+----------------+-------------+ | Alt-Right|
        113534336| @_AltRight_| 19069| | Alt-Right| 1457805708| @TradYouth| 3961| | Alt-Right| 19091173|
```

@scrowder| 295341| | Alt-Right| 28007161| @TheRightStuff| 112| | Alt-Right| 1506831756| @totalfascism| 123| | Alt-Right| 154891961|@NewRightAmerica| 7568| | Anti-Govt| 23658557| @OathKeepers| 14533| | Anti-Govt| 109065990| @RealAlexJones| 453376| | Anti-Govt| 36480404| @drchuckbaldwin| 2035| | Anti-Govt| 130376938| @TomDeweeseAPC| 151| | Anti-Immigrant| 43330802| @AmericanPatrol| 1077| | Anti-Immigrant| 18956212|@FAIRImmigration| 58020| | Anti-Immigrant| 187578616| @horowitz39| 16740| | Anti-LGBT| 239843089| @NCValues| 2357| | Anti-LGBT| 18163042| @FRCdc| 23585| | Anti-LGBT| 86145717| @WBCSaysRepent| 13761| | Anti-LGBT| 42645839|@AmericanFamAssc| 11246| | Anti-LGBT| 25505732| @libertycounsel| 6368| | Anti-LGBT| 63528301| @LouEngle| 55694| | Anti-Muslim| 168541923| @ACTforAmerica| 57108| | Anti-Muslim| 20708260| @securefreedom| 7364| | Anti-Muslim| 19985444| @jihadwatchRS| 52516| | Anti-Muslim| 79516635| @theronedwards| 1262| | Anti-Muslim| 44653060| @frankgaffney| 19803| | Black-Separatist| 260131662| @NuwaubianMoors| 78| | Black-Separatist| 273469546| @LouisFarrakhan| 458148| | Black-Separatist| 100101179|@NewBlackPanthr1| 5717| |Christian-Identity| 85332821|@AmericasPromise| 27994| | Ku-Klux-Klan| 31582401|@MilitantKnights| 491| | Ku-Klux-Klan| 2913151| @KKK| 1020| | Neo-Nazi| 3349682675| @whitebriton| 2408| | Neo-Nazi| 189618631| @TCMChurch| 206| | Neo-Nazi| 4502064200| @WLMcom| 218544| | Neo-Nazi| 4716734311|@americavanguard| 1054| | Neo-Nazi| 2246898978| @natsocialist| 27060| | Neo-Nazi|736025718233042945| @AryanNations| 660| | Neo-Nazi| 523934960| @ABKreis3| 9| | Neo-Confederate| 36315753| @dixienetdotorg| 514| | Neo-Confederate| 433462889| @MichaelHill51| 2767| | Racist-Skinhead| 2748378747| @SatanicNazi| 915| | White-Nationalist| 468952611|@MatthewHeimbach| 4989| | White-Nationalist| 271397818| @jartaylor| 18713| | White-Nationalist| 1152375114| @CofCCOhio| 276| | White-Nationalist| 1554897007| @Aryan_Brother| 976| | White-Nationalist| 15210689| @BNReviewer| 35059| | White-Nationalist| 322027737| @AmRenaissance| 13559| | White-Nationalist| 346417825| @AFDINational| 1827| | White-Nationalist| 1428792374| @Stormfront_txt| 551| | White-Nationalist| 27522964| @vdare| 19899| | White-Nationalist| 3999537573| @TradWorker| 1006| | White-Nationalist| 402181258|@RichardBSpencer| 19703| +------------------+------------------+----------------+-------------+

```
def computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(allRetweetsSrcIdDstId: DataFrame,
    leaderIDIdeol: DataFrame, politiciansDF: DataFrame, minRTs: Long, minForAveraging: Double):
    DataFrame = {

val RTsOfsplcIDsHere = allRetweetsSrcIdDstId
            .join(leaderIDIdeol,$"LeaderIDLong"===$"OPostUserIDinRT","left_outer")
            .withColumnRenamed("Ideology","OPostUserIdeologyInRT")
            .filter($"OPostUserIdeologyInRT".isNotNull)
            .withColumn("OPostUserIdeologyRTWeight",lit(1.0))

    .groupBy("CPostUserID","OPostUserIdeologyInRT").agg(sum($"OPostUserIdeologyRTWeight").as("
    OPostUserIdeologyRTWeight"))
            .withColumnRenamed("CPostUserID","CPostUserIDInExtremistRT")

val dfHere = allRetweetsSrcIdDstId
  .join(politiciansDF,$"OPostUserIDinRT"===$"id").drop("id")
  .withColumn("OPostUserPoliticalRTWeight",lit(1.0))

    .groupBy("CPostUserID","OPostUserIDInRT","PoliticalScreenName").agg(sum($"OPostUserPolitical
    RTWeight").as("OPostUserPoliticalRTWeight"))
  .join(RTsOfsplcIDsHere,$"CPostUserIDInExtremistRT"===$"CPostUserID")
  .filter($"OPostUserPoliticalRTWeight">minRTs and $"OPostUserIdeologyRTWeight">minRTs)
  //.cache // 37870, 1545 when >9

val polAndIdeolInit0 = politiciansDF.select("PoliticalScreenName")
                .join(leaderIDIdeol.select($"Ideology".as("OPostUserIdeologyInRT")).distinct())
                .withColumn("OPostUserPoliticalRTWeight",lit(0.0))
                .withColumn("OPostUserIdeologyRTWeight",lit(0.0))
                .withColumn("Number_Of_Retweeters",lit(0.0))

val politicianSplcIdeologyNumRetweeters = dfHere.select("PoliticalScreenName","OPostUserIdeologyInRT",
```

```
"OPostUserPoliticalRTWeight","OPostUserIdeologyRTWeight").withColumn("Number_Of_Retweete
rs",lit(1.0))
                              .unionAll(polAndIdeolInit0)
                              .groupBy("PoliticalScreenName","OPostUserIdeologyInRT")

.agg(sum("OPostUserPoliticalRTWeight").as("sumOPostUserPoliticalRTWeight"),
                                sum("OPostUserIdeologyRTWeight").as("sumOPostUserIdeologyRTWeight"),
                                sum("Number_Of_Retweeters").as("sumNumber_Of_Retweeters"))
                              .withColumn("avgOPostUserPoliticalRTWeight",
                                when($"sumNumber_Of_Retweeters">=minForAveraging,
$"sumOPostUserPoliticalRTWeight"/$"sumNumber_Of_Retweeters")
                                .otherwise(lit(0.0)))
                              .withColumn("avgOPostUserIdeologyRTWeight",
                                when($"sumNumber_Of_Retweeters">=minForAveraging,
$"sumOPostUserIdeologyRTWeight"/$"sumNumber_Of_Retweeters")
                                .otherwise(lit(0.0)))

.drop($"sumOPostUserPoliticalRTWeight").drop($"sumOPostUserIdeologyRTWeight")
                              .orderBy("PoliticalScreenName","OPostUserIdeologyInRT")

politicianSplcIdeologyNumRetweeters
}

//display(politicianSplcIdeologyNumRetweeters)
val minRTNumber = 2
val minForAveraging = 30.0
val obsStats = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(allRetweets2016SrcIdDstId,
      stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber, minForAveraging)
```

BernieSanders	Alt-Right	0
BernieSanders	Anti-Govt	2
BernieSanders	Anti-Immigrant	52
BernieSanders	Anti-LGBT	1
BernieSanders	Anti-Muslim	3
BernieSanders	Black-Separatist	69
BernieSanders	Christian-Identity	3
BernieSanders	Ku-Klux-Klan	0
BernieSanders	Neo-Confederate	0
BernieSanders	Neo-Nazi	0
BernieSanders	Racist-Skinhead	0
BernieSanders	White-Nationalist	10
HillaryClinton	Alt-Right	0
HillaryClinton	Anti-Govt	5

HillaryClinton	Anti-Immigrant	142
HillaryClinton	Anti-LGBT	4
HillaryClinton	Anti-Muslim	4
HillaryClinton	Black-Separatist	109
HillaryClinton	Christian-Identity	5
HillaryClinton	Ku-Klux-Klan	0
HillaryClinton	Neo-Confederate	0
HillaryClinton	Neo-Nazi	2
HillaryClinton	Racist-Skinhead	0
HillaryClinton	White-Nationalist	23
SpeakerRyan	Alt-Right	1
SpeakerRyan	Anti-Govt	7
SpeakerRyan	Anti-Immigrant	442
SpeakerRyan	Anti-LGBT	22
SpeakerRyan	Anti-Muslim	27
SpeakerRyan	Black-Separatist	6
SpeakerRyan	Christian-Identity	1
SpeakerRyan	Ku-Klux-Klan	0
SpeakerRyan	Neo-Confederate	0
SpeakerRyan	Neo-Nazi	0
SpeakerRyan	Racist-Skinhead	0
SpeakerRyan	White-Nationalist	12
realDonaldTrump	Alt-Right	54
realDonaldTrump	Anti-Govt	239
realDonaldTrump	Anti-Immigrant	4217
realDonaldTrump	Anti-LGBT	234
realDonaldTrump	Anti-Muslim	389
realDonaldTrump	Black-Separatist	169
realDonaldTrump	Christian-Identity	1
realDonaldTrump	Ku-Klux-Klan	0

realDonaldTrump	Neo-Confederate	0
realDonaldTrump	Neo-Nazi	118
realDonaldTrump	Racist-Skinhead	0
realDonaldTrump	White-Nationalist	1010
tedcruz	Alt-Right	5
tedcruz	Anti-Govt	10
tedcruz	Anti-Immigrant	360
tedcruz	Anti-LGBT	51
tedcruz	Anti-Muslim	47
tedcruz	Black-Separatist	2
tedcruz	Christian-Identity	0
tedcruz	Ku-Klux-Klan	0
tedcruz	Neo-Confederate	0
tedcruz	Neo-Nazi	2
tedcruz	Racist-Skinhead	0
tedcruz	White-Nationalist	17
PoliticalScreenName	**OPostUserIdeologyInRT**	**sumNumber_Of_Retweeters**

```
var minRTNumber = 1
var colName="NRTr"+minRTNumber.toString()
val minForAveraging = 30.0
var obsStats1thru9 = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(allRetweets2016SrcIdDstId,
        stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber,
        minForAveraging).select($"PoliticalScreenName",$"OPostUserIdeologyInRT",$"sumNumber_Of_Ret
        weeters".as(colName))

for (minRTNumber <- Seq(2,3,4,5,6,7,8,9)) {
  println(minRTNumber)
  colName="NRTr"+minRTNumber.toString()
  obsStats1thru9 =
        obsStats1thru9.join(computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(allRetweets2016SrcI
        dDstId, stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber,
        minForAveraging).select($"PoliticalScreenName",$"OPostUserIdeologyInRT",$"sumNumber_Of_Ret
        weeters".as(colName)),Seq("PoliticalScreenName","OPostUserIdeologyInRT"))
}

2 3 4 5 6 7 8 9 minRTNumber: Int = 1 colName: String = NRTr9 minForAveraging: Double = 30.0
        obsStats1thru9: org.apache.spark.sql.DataFrame = [PoliticalScreenName: string,
        OPostUserIdeologyInRT: string, NRTr1: double, NRTr2: double, NRTr3: double, NRTr4: double,
        NRTr5: double, NRTr6: double, NRTr7: double, NRTr8: double, NRTr9: double]
obsStats1thru9.cache().count
```

```
res7: Long = 60
display(obsStats1thru9
  .filter(($"OPostUserIdeologyInRT" !== "Ku-Klux-Klan") && ($"OPostUserIdeologyInRT" !== "Neo-
        Confederate") && ($"OPostUserIdeologyInRT" !== "Christian-Identity") &&
        ($"OPostUserIdeologyInRT" !== "Racist-
        Skinhead")).orderBy($"PoliticalScreenName",$"OPostUserIdeologyInRT")
)
```

BernieSanders	Alt-Right	1	0	0	0	0
BernieSanders	Anti-Govt	7	2	1	0	0
BernieSanders	Anti-Immigrant	150	52	24	15	12
BernieSanders	Anti-LGBT	7	1	1	1	1
BernieSanders	Anti-Muslim	8	3	1	0	0
BernieSanders	Black-Separatist	158	69	36	22	10
BernieSanders	Neo-Nazi	2	0	0	0	0
BernieSanders	White-Nationalist	44	10	3	0	0
HillaryClinton	Alt-Right	2	0	0	0	0
HillaryClinton	Anti-Govt	17	5	3	3	2
HillaryClinton	Anti-Immigrant	368	142	72	44	33
HillaryClinton	Anti-LGBT	17	4	2	1	1
HillaryClinton	Anti-Muslim	21	4	2	0	0
HillaryClinton	Black-Separatist	245	109	58	40	31
HillaryClinton	Neo-Nazi	8	2	0	0	0
HillaryClinton	White-Nationalist	71	23	11	9	4
SpeakerRyan	Alt-Right	2	1	0	0	0
SpeakerRyan	Anti-Govt	21	7	3	2	2
SpeakerRyan	Anti-Immigrant	741	442	283	204	155
SpeakerRyan	Anti-LGBT	47	22	12	5	4
SpeakerRyan	Anti-Muslim	48	27	18	13	12
SpeakerRyan	Black-Separatist	12	6	5	5	4
SpeakerRyan	Neo-Nazi	1	0	0	0	0
SpeakerRyan	White-Nationalist	30	12	9	6	5
realDonaldTrump	Alt-Right	100	54	32	22	15
realDonaldTrump	Anti-Govt	429	239	149	107	83

PoliticalScreenName	OPostUserIdeologyInRT	NRTr1	NRTr	NRTr3	NRTr4	NRTr5
realDonaldTrump	Anti-Immigrant	6584	4217	2997	2314	1856
realDonaldTrump	Anti-LGBT	396	234	168	121	96
realDonaldTrump	Anti-Muslim	645	389	274	215	176
realDonaldTrump	Black-Separatist	279	169	106	69	47
realDonaldTrump	Neo-Nazi	246	118	71	45	31
realDonaldTrump	White-Nationalist	1623	1010	699	548	442
tedcruz	Alt-Right	15	5	3	3	2
tedcruz	Anti-Govt	37	10	6	4	2
tedcruz	Anti-Immigrant	724	360	209	133	88
tedcruz	Anti-LGBT	110	51	33	23	15
tedcruz	Anti-Muslim	97	47	33	21	13
tedcruz	Black-Separatist	7	2	1	1	1
tedcruz	Neo-Nazi	5	2	0	0	0
tedcruz	White-Nationalist	51	17	6	4	1

```
val Stats0 = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(
    crossWiresrcIdDstIdRetweetsDFAtRandom(allRetweets2016SrcIdDstId,"OPostUserIDinRT","CPostUserId"),
                stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber, minForAveraging
                )
      .rdd.map { case Row(pol: String, ide: String, numRTrs: Double, avgPolRTs: Double, avgIdeRTs: Double) => (pol+","+ide, (numRTrs,avgPolRTs,avgIdeRTs)) }.collectAsMap()
Stats0: scala.collection.Map[String,(Double, Double, Double)] = Map(tedcruz,Neo-Nazi -> (7.0,0.0,0.0), SpeakerRyan,Black-Separatist -> (3373.0,2.8553216721019865,3.087459235102283), BernieSanders,Anti-Govt -> (38.0,20.289473684210527,2.0), realDonaldTrump,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,Anti-Immigrant -> (8782.0,13.705078569801868,2.5751537235253927), SpeakerRyan,Anti-Govt -> (16.0,0.0,0.0), tedcruz,Anti-LGBT -> (97.0,3.0721649484536084,2.1752577319587627), tedcruz,Anti-Muslim -> (58.0,3.2586206896551726,2.1379310344827585), tedcruz,Alt-Right -> (0.0,0.0,0.0), realDonaldTrump,Neo-Confederate -> (0.0,0.0,0.0), realDonaldTrump,Anti-Muslim -> (194.0,162.63917525773195,2.082474226804124), tedcruz,White-Nationalist -> (252.0,2.9087301587301586,2.257936507936508), SpeakerRyan,Neo-Nazi -> (13.0,0.0,0.0), realDonaldTrump,Anti-Immigrant -> (9375.0,100.41365333333333,2.54112), realDonaldTrump,Anti-LGBT -> (314.0,152.93949044585986,2.0987261146496814), HillaryClinton,Anti-Muslim -> (193.0,76.39378238341969,2.082901554404145), HillaryClinton,Anti-LGBT -> (312.0,71.89102564102564,2.0993589743589745), BernieSanders,Christian-Identity -> (2.0,0.0,0.0), HillaryClinton,Neo-Nazi -> (23.0,0.0,0.0), HillaryClinton,Black-Separatist -> (11542.0,45.05241725870733,2.627967423323514), SpeakerRyan,Anti-Muslim -> (85.0,3.4235294117647057,2.1176470588235294), tedcruz,Anti-Govt -> (16.0,0.0,0.0), SpeakerRyan,Neo-Confederate -> (0.0,0.0,0.0), HillaryClinton,Christian-Identity -> (2.0,0.0,0.0),
```

```
        BernieSanders,Anti-Muslim -> (189.0,21.306878306878307,2.0846560846560847),
        SpeakerRyan,Racist-Skinhead -> (0.0,0.0,0.0), SpeakerRyan,White-Nationalist ->
        (343.0,3.358600583090379,2.2361516034985423), tedcruz,Ku-Klux-Klan -> (0.0,0.0,0.0),
        realDonaldTrump,Alt-Right -> (3.0,0.0,0.0), HillaryClinton,White-Nationalist ->
        (903.0,63.692137320044296,2.1605758582502768), tedcruz,Black-Separatist ->
        (2302.0,2.6155516941789747,3.2037358818418764), realDonaldTrump,Christian-Identity ->
        (2.0,0.0,0.0), tedcruz,Christian-Identity -> (0.0,0.0,0.0), SpeakerRyan,Anti-Immigrant ->
        (2851.0,2.901788846018941,2.9277446509996494), realDonaldTrump,Black-Separatist ->
        (11656.0,95.81571722717914,2.621997254632807), HillaryClinton,Alt-Right -> (3.0,0.0,0.0),
        HillaryClinton,Anti-Govt -> (39.0,72.33333333333333,2.0), SpeakerRyan,Ku-Klux-Klan ->
        (0.0,0.0,0.0), HillaryClinton,Anti-Immigrant -> (9290.0,47.25543595263724,2.5458557588805166),
        realDonaldTrump,Neo-Nazi -> (23.0,0.0,0.0), HillaryClinton,Ku-Klux-Klan -> (0.0,0.0,0.0),
        tedcruz,Racist-Skinhead -> (0.0,0.0,0.0), tedcruz,Anti-Immigrant ->
        (1965.0,2.6417302798982187,3.0396946564885496), tedcruz,Neo-Confederate -> (0.0,0.0,0.0),
        SpeakerRyan,Christian-Identity -> (0.0,0.0,0.0), BernieSanders,Racist-Skinhead -> (0.0,0.0,0.0),
        realDonaldTrump,White-Nationalist -> (910.0,135.03846153846155,2.159340659340659),
        realDonaldTrump,Anti-Govt -> (40.0,150.4,2.0), BernieSanders,Black-Separatist ->
        (10763.0,13.178296014122457,2.668122270742358), BernieSanders,Neo-Confederate -> (0.0,0.0,0.0),
        BernieSanders,Alt-Right -> (3.0,0.0,0.0), BernieSanders,Neo-Nazi -> (22.0,0.0,0.0),
        BernieSanders,Anti-LGBT -> (300.0,20.753333333333334,2.1), SpeakerRyan,Anti-LGBT ->
        (133.0,3.6165413533834587,2.18796992481203), realDonaldTrump,Ku-Klux-Klan -> (0.0,0.0,0.0),
        HillaryClinton,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,White-Nationalist ->
        (868.0,18.099078341013826,2.1670506912442398), SpeakerRyan,Alt-Right -> (1.0,0.0,0.0),
        HillaryClinton,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Ku-Klux-Klan -> (0.0,0.0,0.0))
val Stats1 = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(

        cutAndReWiresrcIdDstIdRetweetsDFAtRandom(allRetweets2016SrcIdDstId,"OPostUserIDinRT","CP
        ostUserId"),
                       stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber,
        minForAveraging
                       )
           .rdd.map { case Row(pol: String, ide: String, numRTrs: Double, avgPolRTs: Double, avgIdeRTs:
        Double) => (pol+","+ide, (numRTrs,avgPolRTs,avgIdeRTs)) }.collectAsMap()
Stats1: scala.collection.Map[String,(Double, Double, Double)] = Map(tedcruz,Neo-Nazi -> (5.0,0.0,0.0),
        SpeakerRyan,Black-Separatist -> (3449.0,2.8190779936213395,3.0742244128732965),
        BernieSanders,Anti-Govt -> (44.0,25.727272727272727,2.0), realDonaldTrump,Racist-Skinhead ->
        (0.0,0.0,0.0), BernieSanders,Anti-Immigrant -> (8739.0,13.864400961208377,2.5679139489644123),
        SpeakerRyan,Anti-Govt -> (24.0,0.0,0.0), tedcruz,Anti-LGBT ->
        (84.0,3.0714285714285716,2.1666666666666665), tedcruz,Anti-Muslim ->
        (72.0,3.0972222222222223,2.0833333333333335), tedcruz,Alt-Right -> (0.0,0.0,0.0),
        realDonaldTrump,Neo-Confederate -> (0.0,0.0,0.0), realDonaldTrump,Anti-Muslim ->
        (209.0,165.11483253588517,2.0526315789473686), tedcruz,White-Nationalist ->
        (271.0,2.937269372693727,2.217712177121771), SpeakerRyan,Neo-Nazi -> (10.0,0.0,0.0),
        realDonaldTrump,Anti-Immigrant -> (9368.0,100.72256618274979,2.5356532877882154),
        realDonaldTrump,Anti-LGBT -> (312.0,145.51602564102564,2.0993589743589745),
        HillaryClinton,Anti-Muslim -> (209.0,77.01435406698565,2.0526315789473686),
        HillaryClinton,Anti-LGBT -> (312.0,67.11217948717949,2.0993589743589745),
        BernieSanders,Christian-Identity -> (1.0,0.0,0.0), HillaryClinton,Neo-Nazi -> (23.0,0.0,0.0),
        HillaryClinton,Black-Separatist -> (11569.0,44.72530037168295,2.6179445068718126),
        SpeakerRyan,Anti-Muslim -> (91.0,3.934065934065934,2.087912087912088), tedcruz,Anti-Govt ->
        (19.0,0.0,0.0), SpeakerRyan,Neo-Confederate -> (0.0,0.0,0.0), HillaryClinton,Christian-Identity ->
        (1.0,0.0,0.0), BernieSanders,Anti-Muslim -> (201.0,21.766169154228855,2.054726368159204),
        SpeakerRyan,Racist-Skinhead -> (0.0,0.0,0.0), SpeakerRyan,White-Nationalist ->
        (402.0,3.1417910447761193,2.1791044776119404), tedcruz,Ku-Klux-Klan -> (0.0,0.0,0.0),
        realDonaldTrump,Alt-Right -> (1.0,0.0,0.0), HillaryClinton,White-Nationalist ->
        (910.0,64.64615384615385,2.1307692307692307), tedcruz,Black-Separatist ->
        (2278.0,2.6334503950834063,3.1733977172958734), realDonaldTrump,Christian-Identity ->
        (1.0,0.0,0.0), tedcruz,Christian-Identity -> (0.0,0.0,0.0), SpeakerRyan,Anti-Immigrant ->
        (2940.0,2.844557823129252,2.869047619047619), realDonaldTrump,Black-Separatist ->
        (11712.0,94.95184426229508,2.610655737704918), HillaryClinton,Alt-Right -> (1.0,0.0,0.0),
```

HillaryClinton,Anti-Govt -> (45.0,86.42222222222222,2.0), SpeakerRyan,Ku-Klux-Klan -> (0.0,0.0,0.0), HillaryClinton,Anti-Immigrant -> (9272.0,47.2858067299396,2.540983606557377), realDonaldTrump,Neo-Nazi -> (23.0,0.0,0.0), HillaryClinton,Ku-Klux-Klan -> (0.0,0.0,0.0), tedcruz,Racist-Skinhead -> (0.0,0.0,0.0), tedcruz,Anti-Immigrant -> (1944.0,2.6502057613168724,2.991255144032922), tedcruz,Neo-Confederate -> (0.0,0.0,0.0), SpeakerRyan,Christian-Identity -> (1.0,0.0,0.0), BernieSanders,Racist-Skinhead -> (0.0,0.0,0.0), realDonaldTrump,White-Nationalist -> (916.0,139.96724890829694,2.1299126637554586), realDonaldTrump,Anti-Govt -> (45.0,189.46666666666667,2.0), BernieSanders,Black-Separatist -> (10846.0,13.198229762124285,2.6538816153420615), BernieSanders,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Alt-Right -> (1.0,0.0,0.0), BernieSanders,Neo-Nazi -> (22.0,0.0,0.0), BernieSanders,Anti-LGBT -> (303.0,18.874587458745875,2.102310231023102), SpeakerRyan,Anti-LGBT -> (135.0,3.2,2.162962962962963), realDonaldTrump,Ku-Klux-Klan -> (0.0,0.0,0.0), HillaryClinton,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,White-Nationalist -> (879.0,18.898748577929464,2.135381114903299), SpeakerRyan,Alt-Right -> (1.0,0.0,0.0), HillaryClinton,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Ku-Klux-Klan -> (0.0,0.0,0.0))

```
val allRetweets2016SrcIdDstIdIndexed = allRetweets2016SrcIdDstId.rdd.map{ case Row(s: Long, d: Long) =>
    (s, d) }
                .zipWithIndex.map(tuple => (tuple._1._1, tuple._1._2, tuple._2))
                .toDF("OPostUserIDinRT","CPostUserId","ID").cache()
allRetweets2016SrcIdDstIdIndexed.count
```

allRetweets2016SrcIdDstIdIndexed: org.apache.spark.sql.DataFrame = [OPostUserIDinRT: bigint, CPostUserId: bigint, ID: bigint] res9: Long = 12984331

```
val Stats1 = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(

    cutAndReWiresrcIdDstIdRetweetsIndexedDFAtRandom(allRetweets2016SrcIdDstIdIndexed,"OPostUserIDinRT","CPostUserId","ID"),
                    stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber,
    minForAveraging
                    )
        .rdd.map { case Row(pol: String, ide: String, numRTrs: Double, avgPolRTs: Double, avgIdeRTs:
    Double) => (pol+","+ide, (numRTrs,avgPolRTs,avgIdeRTs)) }.collectAsMap()
```

Stats1: scala.collection.Map[String,(Double, Double, Double)] = Map(tedcruz,Neo-Nazi -> (7.0,0.0,0.0), SpeakerRyan,Black-Separatist -> (3373.0,2.824488585828639,3.0936851467536317), BernieSanders,Anti-Govt -> (34.0,26.61764705882353,2.0294117647058822), realDonaldTrump,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,Anti-Immigrant -> (8586.0,13.833100395993478,2.584556254367575), SpeakerRyan,Anti-Govt -> (18.0,0.0,0.0), tedcruz,Anti-LGBT -> (98.0,3.4285714285714284,2.2551020408163267), tedcruz,Anti-Muslim -> (60.0,3.15,2.066666666666667), tedcruz,Alt-Right -> (2.0,0.0,0.0), realDonaldTrump,Neo-Confederate -> (0.0,0.0,0.0), realDonaldTrump,Anti-Muslim -> (184.0,156.1304347826087,2.0489130434782608), tedcruz,White-Nationalist -> (234.0,3.034188034188034,2.3119658119658117), SpeakerRyan,Neo-Nazi -> (11.0,0.0,0.0), realDonaldTrump,Anti-Immigrant -> (9225.0,101.24433604336043,2.5487262872628724), realDonaldTrump,Anti-LGBT -> (297.0,172.4983164983165,2.1178451178451176), HillaryClinton,Anti-Muslim -> (183.0,72.79234972677595,2.0491803278688523), HillaryClinton,Anti-LGBT -> (295.0,81.56271186440678,2.1186440677966103), BernieSanders,Christian-Identity -> (5.0,0.0,0.0), HillaryClinton,Neo-Nazi -> (20.0,0.0,0.0), HillaryClinton,Black-Separatist -> (11546.0,45.29759223973671,2.6425601940065824), SpeakerRyan,Anti-Muslim -> (84.0,3.3452380952380953,2.0714285714285716), tedcruz,Anti-Govt -> (12.0,0.0,0.0), SpeakerRyan,Neo-Confederate -> (0.0,0.0,0.0), HillaryClinton,Christian-Identity -> (5.0,0.0,0.0), BernieSanders,Anti-Muslim -> (178.0,20.668539325842698,2.050561797752809), SpeakerRyan,Racist-Skinhead -> (0.0,0.0,0.0), SpeakerRyan,White-Nationalist -> (349.0,3.3638968481375358,2.2578796561604584), tedcruz,Ku-Klux-Klan -> (0.0,0.0,0.0), realDonaldTrump,Alt-Right -> (4.0,0.0,0.0), HillaryClinton,White-Nationalist -> (890.0,63.52022471910112,2.150561797752809), tedcruz,Black-Separatist -> (2254.0,2.627329192546584,3.199645075421473), realDonaldTrump,Christian-Identity -> (5.0,0.0,0.0), tedcruz,Christian-Identity -> (3.0,0.0,0.0), SpeakerRyan,Anti-Immigrant -> (2875.0,2.8671304347826085,2.9356521739130437), realDonaldTrump,Black-Separatist -> (11679.0,96.12620943573936,2.635585238462197), HillaryClinton,Alt-Right -> (4.0,0.0,0.0), HillaryClinton,Anti-Govt -> (36.0,90.19444444444444,2.0277777777777777), SpeakerRyan,Ku-Klux-

```
Klan -> (0.0,0.0,0.0), HillaryClinton,Anti-Immigrant -> (9148.0,47.60034980323568,2.5533449934411894), realDonaldTrump,Neo-Nazi -> (21.0,0.0,0.0), HillaryClinton,Ku-Klux-Klan -> (0.0,0.0,0.0), tedcruz,Racist-Skinhead -> (0.0,0.0,0.0), tedcruz,Anti-Immigrant -> (1960.0,2.6311224489795917,2.964795918367347), tedcruz,Neo-Confederate -> (0.0,0.0,0.0), SpeakerRyan,Christian-Identity -> (3.0,0.0,0.0), BernieSanders,Racist-Skinhead -> (0.0,0.0,0.0), realDonaldTrump,White-Nationalist -> (894.0,135.44295302013424,2.149888143176734), realDonaldTrump,Anti-Govt -> (36.0,192.75,2.0277777777777777), BernieSanders,Black-Separatist -> (10854.0,13.177353970886308,2.679288741477796), BernieSanders,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Alt-Right -> (4.0,0.0,0.0), BernieSanders,Neo-Nazi -> (20.0,0.0,0.0), BernieSanders,Anti-LGBT -> (288.0,22.684027777777778,2.1215277777777777), SpeakerRyan,Anti-LGBT -> (130.0,4.1,2.1769230769230767), realDonaldTrump,Ku-Klux-Klan -> (0.0,0.0,0.0), HillaryClinton,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,White-Nationalist -> (868.0,17.828341013824886,2.154377880184332), SpeakerRyan,Alt-Right -> (1.0,0.0,0.0), HillaryClinton,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Ku-Klux-Klan -> (0.0,0.0,0.0))
import scala.util.Sorting.quickSort
val minRTNumber = 2
val minForAveraging = 30.0
val obsStats = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(allRetweets2016SrcIdDstId, stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber, minForAveraging)
  .rdd.map { case Row(pol: String, ide: String, numRTrs: Double, avgPolRTs: Double, avgIdeRTs: Double) => (pol+","+ide, (numRTrs,avgPolRTs,avgIdeRTs)) }.collectAsMap()
val N=1000
val MutableMapOfHists: scala.collection.mutable.Map[String,Array[(Double,Double,Double)]] = scala.collection.mutable.Map()
val myMutableMap = collection.mutable.Map() ++ obsStats
for (k <- myMutableMap.keys){// initialize histograms for N replicates
  //println(k)
  MutableMapOfHists(k) = Array.fill(N){(0.0,0.0,0.0)}
 }

 for (i <- 0 to N-1) {
    //Randomize
    val Stats = computeThoseWhoRetweetIdeologyleadersAndPoliticians3D(

cutAndReWiresrcIdDstIdRetweetsIndexedDFAtRandom(allRetweets2016SrcIdDstIdIndexed,"OPostUserIDinRT","CPostUserId","ID"),
                        stdSplcLeaderIDAndIdeology, politicalAccountsDF, minRTNumber, minForAveraging
                        )
        .rdd.map { case Row(pol: String, ide: String, numRTrs: Double, avgPolRTs: Double, avgIdeRTs: Double) => (pol+","+ide, (numRTrs,avgPolRTs,avgIdeRTs)) }.collectAsMap()
    for (k <- Stats.keys){
     MutableMapOfHists(k)(i) = Stats(k) //total
    }

  }
import scala.util.Sorting.quickSort minRTNumber: Int = 2 minForAveraging: Double = 30.0 obsStats: scala.collection.Map[String,(Double, Double, Double)] = Map(tedcruz,Neo-Nazi -> (2.0,0.0,0.0), SpeakerRyan,Black-Separatist -> (6.0,0.0,0.0), BernieSanders,Anti-Govt -> (2.0,0.0,0.0), realDonaldTrump,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,Anti-Immigrant -> (52.0,7.903846153846154,14.51923076923077), SpeakerRyan,Anti-Govt -> (7.0,0.0,0.0), tedcruz,Anti-LGBT -> (51.0,6.529411764705882,10.627450980392156), tedcruz,Anti-Muslim -> (47.0,6.531914893617022,12.340425531914894), tedcruz,Alt-Right -> (5.0,0.0,0.0), realDonaldTrump,Neo-Confederate -> (0.0,0.0,0.0), realDonaldTrump,Anti-Muslim -> (389.0,51.30848329048843,10.169665809768638), tedcruz,White-Nationalist -> (17.0,0.0,0.0), SpeakerRyan,Neo-Nazi -> (0.0,0.0,0.0), realDonaldTrump,Anti-Immigrant -> (4217.0,73.25847759070429,11.881669433246383), realDonaldTrump,Anti-LGBT ->
```

(234.0,42.69230769230769,9.786324786324787), HillaryClinton,Anti-Muslim -> (4.0,0.0,0.0), HillaryClinton,Anti-LGBT -> (4.0,0.0,0.0), BernieSanders,Christian-Identity -> (3.0,0.0,0.0), HillaryClinton,Neo-Nazi -> (2.0,0.0,0.0), HillaryClinton,Black-Separatist -> (109.0,18.201834862385322,10.642201834862385), SpeakerRyan,Anti-Muslim -> (27.0,0.0,0.0), tedcruz,Anti-Govt -> (10.0,0.0,0.0), SpeakerRyan,Neo-Confederate -> (0.0,0.0,0.0), HillaryClinton,Christian-Identity -> (5.0,0.0,0.0), BernieSanders,Anti-Muslim -> (3.0,0.0,0.0), SpeakerRyan,Racist-Skinhead -> (0.0,0.0,0.0), SpeakerRyan,White-Nationalist -> (12.0,0.0,0.0), tedcruz,Ku-Klux-Klan -> (0.0,0.0,0.0), realDonaldTrump,Alt-Right -> (54.0,52.96296296296296,6.648148148148148), HillaryClinton,White-Nationalist -> (23.0,0.0,0.0), tedcruz,Black-Separatist -> (2.0,0.0,0.0), realDonaldTrump,Christian-Identity -> (1.0,0.0,0.0), tedcruz,Christian-Identity -> (0.0,0.0,0.0), SpeakerRyan,Anti-Immigrant -> (442.0,12.438914027149321,16.536199095022624), realDonaldTrump,Black-Separatist -> (169.0,31.11242603550296,10.95266272189349), HillaryClinton,Alt-Right -> (0.0,0.0,0.0), HillaryClinton,Anti-Govt -> (5.0,0.0,0.0), SpeakerRyan,Ku-Klux-Klan -> (0.0,0.0,0.0), HillaryClinton,Anti-Immigrant -> (142.0,15.119718309859154,14.408450704225352), realDonaldTrump,Neo-Nazi -> (118.0,27.661016949152543,6.288135593220339), HillaryClinton,Ku-Klux-Klan -> (0.0,0.0,0.0), tedcruz,Racist-Skinhead -> (0.0,0.0,0.0), tedcruz,Anti-Immigrant -> (360.0,6.122222222222222,19.51388888888889), tedcruz,Neo-Confederate -> (0.0,0.0,0.0), SpeakerRyan,Christian-Identity -> (1.0,0.0,0.0), BernieSanders,Racist-Skinhead -> (0.0,0.0,0.0), realDonaldTrump,White-Nationalist -> (1010.0,48.526732673267325,9.973267326732673), realDonaldTrump,Anti-Govt -> (239.0,92.93305439330544,6.510460251046025), BernieSanders,Black-Separatist -> (69.0,7.869565217391305,7.826086956521739), BernieSanders,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Alt-Right -> (0.0,0.0,0.0), BernieSanders,Neo-Nazi -> (0.0,0.0,0.0), BernieSanders,Anti-LGBT -> (1.0,0.0,0.0), SpeakerRyan,Anti-LGBT -> (22.0,0.0,0.0), realDonaldTrump,Ku-Klux-Klan -> (0.0,0.0,0.0), HillaryClinton,Racist-Skinhead -> (0.0,0.0,0.0), BernieSanders,White-Nationalist -> (10.0,0.0,0.0), SpeakerRyan,Alt-Right -> (1.0,0.0,0.0), HillaryClinton,Neo-Confederate -> (0.0,0.0,0.0), BernieSanders,Ku-Klux-Klan -> (0.0,0.0,0.0)) N: Int = 1000 MutableMapOfHists: scala.collection.mutable.Map[String,Array[(Double, Double, Double)]] = Map(tedcruz,Neo-Nazi -> Array((0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (1.0,0.0,0.0), (0.0,0.0,0.0), (2.0,0.0,0.0), (0.0,0.0,0.0), (0.0,0.0,0.0), (1.0,0.0,0.0),

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        (892.0,3.9529147982062782,4.30...
// augmented
// minRTNumber = 4 // 2
// minForAveraging = 30.0

println(s"politician,ideology, number of users who Retweeted a politician and an ideology-leader more than
        $minRTNumber times : (0.005,0.995) null CI; (if significant and > $minForAveraging) mean number
        of RTs for the 9-week period of the politician: (0.0005,0.9995) null CI ; mean number of RTs for the 9-
        week period of an ideology-leader: (0.005,0.995) null CI")
import scala.collection.immutable.ListMap
val myKeys = ListMap(obsStats.toSeq.sortBy(_._1):_*).keys
for (k <- myKeys){//N=1000
  val hist1 = for ( x <- MutableMapOfHists(k) ) yield x._1 ; quickSort(hist1);
  val hist2 = for ( x <- MutableMapOfHists(k) ) yield x._2 ; quickSort(hist2);
  val hist3 = for ( x <- MutableMapOfHists(k) ) yield x._3 ; quickSort(hist3);
  val o1 = obsStats(k)._1; val o1L = hist1(0); val o1U = hist1(N-1); val o2=obsStats(k)._2; val o2L=hist2(0);
        val o2U=hist2(N-1); val o3=obsStats(k)._3; val o3L=hist3(0); val o3U=hist3(N-1)
  if(o1 > o1U && o1 >= 30.0) println(k+s" $o1 : ($o1L, $o1U)  ;  $o2 : ($o2L, $o2U)  ;  $o3 : ($o3L, $o3U)")
  else println(k+s" $o1 : ($o1L, $o1U)  ")
}
/*
//output was: for N=100, minRTNumber = 4
BernieSanders,Alt-Right 0.0 : (0.0, 0.0)
```

BernieSanders,Anti-Govt 0.0 : (0.0, 1.0)
BernieSanders,Anti-Immigrant 15.0 : (371.0, 477.0)
BernieSanders,Anti-LGBT 1.0 : (0.0, 3.0)
BernieSanders,Anti-Muslim 0.0 : (0.0, 2.0)
BernieSanders,Black-Separatist 22.0 : (647.0, 765.0)
BernieSanders,Christian-Identity 2.0 : (0.0, 0.0)
BernieSanders,Ku-Klux-Klan 0.0 : (0.0, 0.0)
BernieSanders,Neo-Confederate 0.0 : (0.0, 0.0)
BernieSanders,Neo-Nazi 0.0 : (0.0, 1.0)
BernieSanders,Racist-Skinhead 0.0 : (0.0, 0.0)
BernieSanders,White-Nationalist 0.0 : (1.0, 9.0)
HillaryClinton,Alt-Right 0.0 : (0.0, 0.0)
HillaryClinton,Anti-Govt 3.0 : (0.0, 1.0)
HillaryClinton,Anti-Immigrant 44.0 : (374.0, 479.0)
HillaryClinton,Anti-LGBT 1.0 : (0.0, 3.0)
HillaryClinton,Anti-Muslim 0.0 : (0.0, 2.0)
HillaryClinton,Black-Separatist 40.0 : (653.0, 770.0)
HillaryClinton,Christian-Identity 2.0 : (0.0, 0.0)
HillaryClinton,Ku-Klux-Klan 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Confederate 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Nazi 0.0 : (0.0, 1.0)
HillaryClinton,Racist-Skinhead 0.0 : (0.0, 0.0)
HillaryClinton,White-Nationalist 9.0 : (1.0, 9.0)
SpeakerRyan,Alt-Right 0.0 : (0.0, 0.0)
SpeakerRyan,Anti-Govt 2.0 : (0.0, 1.0)
SpeakerRyan,Anti-Immigrant 204.0 : (58.0, 85.0) ; 18.715686274509803 : (6.470588235294118, 7.712121212121212) ; 25.583333333333332 : (6.458333333333333, 7.923076923076923)
SpeakerRyan,Anti-LGBT 5.0 : (0.0, 3.0)
SpeakerRyan,Anti-Muslim 13.0 : (0.0, 1.0)
SpeakerRyan,Black-Separatist 5.0 : (80.0, 119.0)
SpeakerRyan,Christian-Identity 0.0 : (0.0, 0.0)
SpeakerRyan,Ku-Klux-Klan 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Confederate 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Nazi 0.0 : (0.0, 1.0)
SpeakerRyan,Racist-Skinhead 0.0 : (0.0, 0.0)
SpeakerRyan,White-Nationalist 6.0 : (0.0, 7.0)
realDonaldTrump,Alt-Right 22.0 : (0.0, 0.0)
realDonaldTrump,Anti-Govt 107.0 : (0.0, 1.0) ; 114.13084112149532 : (0.0, 0.0) ; 10.439252336448599 : (0.0, 0.0)
realDonaldTrump,Anti-Immigrant 2314.0 : (374.0, 479.0) ; 82.61192739844425 : (228.89485458612975, 248.13189448441247) ; 18.56828003457217 : (5.681614349775785, 5.990361445783132)
realDonaldTrump,Anti-LGBT 121.0 : (0.0, 3.0) ; 52.289256198347104 : (0.0, 0.0) ; 15.024793388429751 : (0.0, 0.0)
realDonaldTrump,Anti-Muslim 215.0 : (0.0, 2.0) ; 59.15348837209302 : (0.0, 0.0) ; 15.525581395348837 : (0.0, 0.0)
realDonaldTrump,Black-Separatist 69.0 : (653.0, 770.0)
realDonaldTrump,Christian-Identity 0.0 : (0.0, 0.0)
realDonaldTrump,Ku-Klux-Klan 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Confederate 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Nazi 45.0 : (0.0, 1.0) ; 41.8 : (0.0, 0.0) ; 9.844444444444445 : (0.0, 0.0)
realDonaldTrump,Racist-Skinhead 0.0 : (0.0, 0.0)
realDonaldTrump,White-Nationalist 548.0 : (1.0, 9.0) ; 59.49087591240876 : (0.0, 0.0) ; 14.64963503649635 : (0.0, 0.0)
tedcruz,Alt-Right 3.0 : (0.0, 0.0)
tedcruz,Anti-Govt 4.0 : (0.0, 1.0)

tedcruz,Anti-Immigrant 133.0 : (21.0, 49.0) ; 8.81203007518797 : (0.0, 8.0) ; 35.774436090225564 : (0.0, 9.580645161290322)
tedcruz,Anti-LGBT 23.0 : (0.0, 3.0)
tedcruz,Anti-Muslim 21.0 : (0.0, 1.0)
tedcruz,Black-Separatist 1.0 : (32.0, 61.0)
tedcruz,Christian-Identity 0.0 : (0.0, 0.0)
tedcruz,Ku-Klux-Klan 0.0 : (0.0, 0.0)
tedcruz,Neo-Confederate 0.0 : (0.0, 0.0)
tedcruz,Neo-Nazi 0.0 : (0.0, 1.0)
tedcruz,Racist-Skinhead 0.0 : (0.0, 0.0)
tedcruz,White-Nationalist 4.0 : (0.0, 6.0)
//////////////////// N=1000
politician,ideology, number of users who Retweeted a politician and an ideology-leader more than 4 times : (0.005,0.995) null CI; (if significant and > 30.0) mean number of RTs for the 9-week period of the politician: (0.0005,0.9995) null CI ; mean number of RTs for the 9-week period of an ideology-leader: (0.005,0.995) null CI
BernieSanders,Alt-Right 0.0 : (0.0, 0.0)
BernieSanders,Anti-Govt 0.0 : (0.0, 1.0)
BernieSanders,Anti-Immigrant 15.0 : (369.0, 485.0)
BernieSanders,Anti-LGBT 1.0 : (0.0, 4.0)
BernieSanders,Anti-Muslim 0.0 : (0.0, 3.0)
BernieSanders,Black-Separatist 22.0 : (645.0, 801.0)
BernieSanders,Christian-Identity 2.0 : (0.0, 0.0)
BernieSanders,Ku-Klux-Klan 0.0 : (0.0, 0.0)
BernieSanders,Neo-Confederate 0.0 : (0.0, 0.0)
BernieSanders,Neo-Nazi 0.0 : (0.0, 1.0)
BernieSanders,Racist-Skinhead 0.0 : (0.0, 0.0)
BernieSanders,White-Nationalist 0.0 : (0.0, 10.0)
HillaryClinton,Alt-Right 0.0 : (0.0, 0.0)
HillaryClinton,Anti-Govt 3.0 : (0.0, 1.0)
HillaryClinton,Anti-Immigrant 44.0 : (373.0, 492.0)
HillaryClinton,Anti-LGBT 1.0 : (0.0, 4.0)
HillaryClinton,Anti-Muslim 0.0 : (0.0, 3.0)
HillaryClinton,Black-Separatist 40.0 : (649.0, 808.0)
HillaryClinton,Christian-Identity 2.0 : (0.0, 0.0)
HillaryClinton,Ku-Klux-Klan 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Confederate 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Nazi 0.0 : (0.0, 1.0)
HillaryClinton,Racist-Skinhead 0.0 : (0.0, 0.0)
HillaryClinton,White-Nationalist 9.0 : (0.0, 10.0)
SpeakerRyan,Alt-Right 0.0 : (0.0, 0.0)
SpeakerRyan,Anti-Govt 2.0 : (0.0, 1.0)
SpeakerRyan,Anti-Immigrant 204.0 : (47.0, 95.0) ; 18.715686274509803 : (6.405405405405405, 8.059701492537313) ; 25.583333333333332 : (6.578947368421052, 8.210526315789474)
SpeakerRyan,Anti-LGBT 5.0 : (0.0, 3.0)
SpeakerRyan,Anti-Muslim 13.0 : (0.0, 3.0)
SpeakerRyan,Black-Separatist 5.0 : (72.0, 128.0)
SpeakerRyan,Christian-Identity 0.0 : (0.0, 0.0)
SpeakerRyan,Ku-Klux-Klan 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Confederate 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Nazi 0.0 : (0.0, 1.0)
SpeakerRyan,Racist-Skinhead 0.0 : (0.0, 0.0)
SpeakerRyan,White-Nationalist 6.0 : (0.0, 8.0)
realDonaldTrump,Alt-Right 22.0 : (0.0, 0.0)
realDonaldTrump,Anti-Govt 107.0 : (0.0, 1.0) ; 114.13084112149532 : (0.0, 0.0) ; 10.439252336448599 : (0.0, 0.0)

realDonaldTrump,Anti-Immigrant 2314.0 : (373.0, 492.0) ; 82.61192739844425 : (225.37303370786518, 252.41935483870967) ; 18.56828003457217 : (5.660508083140877, 6.014778325123153)
realDonaldTrump,Anti-LGBT 121.0 : (0.0, 4.0) ; 52.289256198347104 : (0.0, 0.0) ; 15.024793388429751 : (0.0, 0.0)
realDonaldTrump,Anti-Muslim 215.0 : (0.0, 3.0) ; 59.15348837209302 : (0.0, 0.0) ; 15.525581395348837 : (0.0, 0.0)
realDonaldTrump,Black-Separatist 69.0 : (649.0, 808.0)
realDonaldTrump,Christian-Identity 0.0 : (0.0, 0.0)
realDonaldTrump,Ku-Klux-Klan 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Confederate 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Nazi 45.0 : (0.0, 1.0) ; 41.8 : (0.0, 0.0) ; 9.844444444444445 : (0.0, 0.0)
realDonaldTrump,Racist-Skinhead 0.0 : (0.0, 0.0)
realDonaldTrump,White-Nationalist 548.0 : (0.0, 10.0) ; 59.49087591240876 : (0.0, 0.0) ; 14.64963503649635 : (0.0, 0.0)
tedcruz,Alt-Right 3.0 : (0.0, 0.0)
tedcruz,Anti-Govt 4.0 : (0.0, 1.0)
tedcruz,Anti-Immigrant 133.0 : (18.0, 54.0) ; 8.81203007518797 : (0.0, 8.290322580645162) ; 35.774436090225564 : (0.0, 10.1)
tedcruz,Anti-LGBT 23.0 : (0.0, 3.0)
tedcruz,Anti-Muslim 21.0 : (0.0, 3.0)
tedcruz,Black-Separatist 1.0 : (28.0, 66.0)
tedcruz,Christian-Identity 0.0 : (0.0, 0.0)
tedcruz,Ku-Klux-Klan 0.0 : (0.0, 0.0)
tedcruz,Neo-Confederate 0.0 : (0.0, 0.0)
tedcruz,Neo-Nazi 0.0 : (0.0, 1.0)
tedcruz,Racist-Skinhead 0.0 : (0.0, 0.0)
tedcruz,White-Nationalist 4.0 : (0.0, 7.0)

// N=100, minRTNumber = 2
politician,ideology, number of users who Retweeted a politician and an ideology-leader more than 2 times : (0.005,0.995) null CI; (if significant and > 30.0) mean number of RTs for the 9-week period of the politician: (0.0005,0.9995) null CI ; mean number of RTs for the 9-week period of an ideology-leader: (0.005,0.995) null CI
BernieSanders,Alt-Right 0.0 : (0.0, 1.0)
BernieSanders,Anti-Govt 2.0 : (0.0, 4.0)
BernieSanders,Anti-Immigrant 52.0 : (2872.0, 3130.0)
BernieSanders,Anti-LGBT 1.0 : (13.0, 36.0)
BernieSanders,Anti-Muslim 3.0 : (5.0, 21.0)
BernieSanders,Black-Separatist 69.0 : (4038.0, 4250.0)
BernieSanders,Christian-Identity 3.0 : (0.0, 1.0)
BernieSanders,Ku-Klux-Klan 0.0 : (0.0, 0.0)
BernieSanders,Neo-Confederate 0.0 : (0.0, 0.0)
BernieSanders,Neo-Nazi 0.0 : (0.0, 3.0)
BernieSanders,Racist-Skinhead 0.0 : (0.0, 0.0)
BernieSanders,White-Nationalist 10.0 : (86.0, 135.0)
HillaryClinton,Alt-Right 0.0 : (0.0, 1.0)
HillaryClinton,Anti-Govt 5.0 : (0.0, 4.0)
HillaryClinton,Anti-Immigrant 142.0 : (2933.0, 3202.0)
HillaryClinton,Anti-LGBT 4.0 : (13.0, 36.0)
HillaryClinton,Anti-Muslim 4.0 : (5.0, 21.0)
HillaryClinton,Black-Separatist 109.0 : (4133.0, 4360.0)
HillaryClinton,Christian-Identity 5.0 : (0.0, 1.0)
HillaryClinton,Ku-Klux-Klan 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Confederate 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Nazi 2.0 : (0.0, 3.0)
HillaryClinton,Racist-Skinhead 0.0 : (0.0, 0.0)

HillaryClinton,White-Nationalist 23.0 : (87.0, 137.0)
SpeakerRyan,Alt-Right 1.0 : (0.0, 1.0)
SpeakerRyan,Anti-Govt 7.0 : (0.0, 2.0)
SpeakerRyan,Anti-Immigrant 442.0 : (684.0, 810.0)
SpeakerRyan,Anti-LGBT 22.0 : (4.0, 20.0)
SpeakerRyan,Anti-Muslim 27.0 : (1.0, 11.0)
SpeakerRyan,Black-Separatist 6.0 : (896.0, 1007.0)
SpeakerRyan,Christian-Identity 1.0 : (0.0, 0.0)
SpeakerRyan,Ku-Klux-Klan 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Confederate 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Nazi 0.0 : (0.0, 2.0)
SpeakerRyan,Racist-Skinhead 0.0 : (0.0, 0.0)
SpeakerRyan,White-Nationalist 12.0 : (25.0, 55.0)
realDonaldTrump,Alt-Right 54.0 : (0.0, 1.0) ; 52.96296296296296 : (0.0, 0.0) ; 6.648148148148148 : (0.0, 0.0)
realDonaldTrump,Anti-Govt 239.0 : (0.0, 4.0) ; 92.93305439330544 : (0.0, 0.0) ; 6.510460251046025 : (0.0, 0.0)
realDonaldTrump,Anti-Immigrant 4217.0 : (2937.0, 3204.0) ; 73.25847759070429 : (142.1872, 147.9616782292699) ; 11.881669433246383 : (3.582715253144147, 3.669050051072523)
realDonaldTrump,Anti-LGBT 234.0 : (13.0, 36.0) ; 42.69230769230769 : (0.0, 369.48387096774195) ; 9.786324786324787 : (0.0, 3.193548387096774)
realDonaldTrump,Anti-Muslim 389.0 : (5.0, 21.0) ; 51.30848329048843 : (0.0, 0.0) ; 10.169665809768638 : (0.0, 0.0)
realDonaldTrump,Black-Separatist 169.0 : (4141.0, 4365.0)
realDonaldTrump,Christian-Identity 1.0 : (0.0, 1.0)
realDonaldTrump,Ku-Klux-Klan 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Confederate 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Nazi 118.0 : (0.0, 3.0) ; 27.661016949152543 : (0.0, 0.0) ; 6.288135593220339 : (0.0, 0.0)
realDonaldTrump,Racist-Skinhead 0.0 : (0.0, 0.0)
realDonaldTrump,White-Nationalist 1010.0 : (87.0, 137.0) ; 48.526732673267325 : (205.18548387096774, 288.2298850574713) ; 9.973267326732673 : (3.121495327102804, 3.3636363636363638)
tedcruz,Alt-Right 5.0 : (0.0, 1.0)
tedcruz,Anti-Govt 10.0 : (0.0, 2.0)
tedcruz,Anti-Immigrant 360.0 : (393.0, 480.0)
tedcruz,Anti-LGBT 51.0 : (2.0, 16.0) ; 6.529411764705882 : (0.0, 0.0) ; 10.627450980392156 : (0.0, 0.0)
tedcruz,Anti-Muslim 47.0 : (0.0, 10.0) ; 6.531914893617022 : (0.0, 0.0) ; 12.340425531914894 : (0.0, 0.0)
tedcruz,Black-Separatist 2.0 : (499.0, 598.0)
tedcruz,Christian-Identity 0.0 : (0.0, 0.0)
tedcruz,Ku-Klux-Klan 0.0 : (0.0, 0.0)
tedcruz,Neo-Confederate 0.0 : (0.0, 0.0)
tedcruz,Neo-Nazi 2.0 : (0.0, 2.0)
tedcruz,Racist-Skinhead 0.0 : (0.0, 0.0)
tedcruz,White-Nationalist 17.0 : (16.0, 41.0)

//minRTNumber=2, N=1000
politician,ideology, number of users who Retweeted a politician and an ideology-leader more than 2 times : (0.005,0.995) null CI; (if significant and > 30.0) mean number of RTs for the 9-week period of the politician: (0.0005,0.9995) null CI ; mean number of RTs for the 9-week period of an ideology-leader: (0.005,0.995) null CI
BernieSanders,Alt-Right 0.0 : (0.0, 2.0)
BernieSanders,Anti-Govt 2.0 : (0.0, 5.0)
BernieSanders,Anti-Immigrant 52.0 : (2874.0, 3147.0)
BernieSanders,Anti-LGBT 1.0 : (10.0, 44.0)
BernieSanders,Anti-Muslim 3.0 : (2.0, 24.0)
BernieSanders,Black-Separatist 69.0 : (4003.0, 4274.0)

BernieSanders,Christian-Identity 3.0 : (0.0, 2.0)
BernieSanders,Ku-Klux-Klan 0.0 : (0.0, 0.0)
BernieSanders,Neo-Confederate 0.0 : (0.0, 0.0)
BernieSanders,Neo-Nazi 0.0 : (0.0, 4.0)
BernieSanders,Racist-Skinhead 0.0 : (0.0, 0.0)
BernieSanders,White-Nationalist 10.0 : (78.0, 142.0)
HillaryClinton,Alt-Right 0.0 : (0.0, 2.0)
HillaryClinton,Anti-Govt 5.0 : (0.0, 5.0)
HillaryClinton,Anti-Immigrant 142.0 : (2933.0, 3212.0)
HillaryClinton,Anti-LGBT 4.0 : (10.0, 44.0)
HillaryClinton,Anti-Muslim 4.0 : (2.0, 24.0)
HillaryClinton,Black-Separatist 109.0 : (4113.0, 4388.0)
HillaryClinton,Christian-Identity 5.0 : (0.0, 2.0)
HillaryClinton,Ku-Klux-Klan 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Confederate 0.0 : (0.0, 0.0)
HillaryClinton,Neo-Nazi 2.0 : (0.0, 4.0)
HillaryClinton,Racist-Skinhead 0.0 : (0.0, 0.0)
HillaryClinton,White-Nationalist 23.0 : (79.0, 144.0)
SpeakerRyan,Alt-Right 1.0 : (0.0, 1.0)
SpeakerRyan,Anti-Govt 7.0 : (0.0, 4.0)
SpeakerRyan,Anti-Immigrant 442.0 : (664.0, 834.0)
SpeakerRyan,Anti-LGBT 22.0 : (2.0, 23.0)
SpeakerRyan,Anti-Muslim 27.0 : (0.0, 15.0)
SpeakerRyan,Black-Separatist 6.0 : (860.0, 1034.0)
SpeakerRyan,Christian-Identity 1.0 : (0.0, 1.0)
SpeakerRyan,Ku-Klux-Klan 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Confederate 0.0 : (0.0, 0.0)
SpeakerRyan,Neo-Nazi 0.0 : (0.0, 4.0)
SpeakerRyan,Racist-Skinhead 0.0 : (0.0, 0.0)
SpeakerRyan,White-Nationalist 12.0 : (23.0, 65.0)
realDonaldTrump,Alt-Right 54.0 : (0.0, 2.0) ; 52.96296296296296 : (0.0, 0.0) ; 6.648148148148148 : (0.0, 0.0)
realDonaldTrump,Anti-Govt 239.0 : (0.0, 5.0) ; 92.93305439330544 : (0.0, 0.0) ; 6.510460251046025 : (0.0, 0.0)
realDonaldTrump,Anti-Immigrant 4217.0 : (2936.0, 3213.0) ; 73.25847759070429 : (141.5390826873385, 147.87844036697248) ; 11.881669433246383 : (3.577196382428941, 3.6906005221932117)
realDonaldTrump,Anti-LGBT 234.0 : (10.0, 44.0) ; 42.69230769230769 : (0.0, 420.030303030303) ; 9.786324786324787 : (0.0, 3.388888888888889)
realDonaldTrump,Anti-Muslim 389.0 : (2.0, 24.0) ; 51.30848329048843 : (0.0, 0.0) ; 10.169665809768638 : (0.0, 0.0)
realDonaldTrump,Black-Separatist 169.0 : (4120.0, 4393.0)
realDonaldTrump,Christian-Identity 1.0 : (0.0, 2.0)
realDonaldTrump,Ku-Klux-Klan 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Confederate 0.0 : (0.0, 0.0)
realDonaldTrump,Neo-Nazi 118.0 : (0.0, 4.0) ; 27.661016949152543 : (0.0, 0.0) ; 6.288135593220339 : (0.0, 0.0)
realDonaldTrump,Racist-Skinhead 0.0 : (0.0, 0.0)
realDonaldTrump,White-Nationalist 1010.0 : (79.0, 144.0) ; 48.526732673267325 : (200.2843137254902, 298.63440860215053) ; 9.973267326732673 : (3.0961538461538463, 3.407766990291262)
tedcruz,Alt-Right 5.0 : (0.0, 1.0)
tedcruz,Anti-Govt 10.0 : (0.0, 3.0)
tedcruz,Anti-Immigrant 360.0 : (360.0, 505.0)
tedcruz,Anti-LGBT 51.0 : (1.0, 17.0) ; 6.529411764705882 : (0.0, 0.0) ; 10.627450980392156 : (0.0, 0.0)
tedcruz,Anti-Muslim 47.0 : (0.0, 13.0) ; 6.531914893617022 : (0.0, 0.0) ; 12.340425531914894 : (0.0, 0.0)
tedcruz,Black-Separatist 2.0 : (481.0, 612.0)
tedcruz,Christian-Identity 0.0 : (0.0, 1.0)

tedcruz,Ku-Klux-Klan 0.0 : (0.0, 0.0)
tedcruz,Neo-Confederate 0.0 : (0.0, 0.0)
tedcruz,Neo-Nazi 2.0 : (0.0, 4.0)
tedcruz,Racist-Skinhead 0.0 : (0.0, 0.0)
tedcruz,White-Nationalist 17.0 : (15.0, 47.0)

*/

politician,ideology, number of users who Retweeted a politician and an ideology-leader more than 2 times : (0.005,0.995) null CI; (if significant and > 30.0) mean number of RTs for the 9-week period of the politician: (0.0005,0.9995) null CI ; mean number of RTs for the 9-week period of an ideology-leader: (0.005,0.995) null CI BernieSanders,Alt-Right 0.0 : (0.0, 2.0) BernieSanders,Anti-Govt 2.0 : (0.0, 5.0) BernieSanders,Anti-Immigrant 52.0 : (2874.0, 3147.0) BernieSanders,Anti-LGBT 1.0 : (10.0, 44.0) BernieSanders,Anti-Muslim 3.0 : (2.0, 24.0) BernieSanders,Black-Separatist 69.0 : (4003.0, 4274.0) BernieSanders,Christian-Identity 3.0 : (0.0, 2.0) BernieSanders,Ku-Klux-Klan 0.0 : (0.0, 0.0) BernieSanders,Neo-Confederate 0.0 : (0.0, 0.0) BernieSanders,Neo-Nazi 0.0 : (0.0, 4.0) BernieSanders,Racist-Skinhead 0.0 : (0.0, 0.0) BernieSanders,White-Nationalist 10.0 : (78.0, 142.0) HillaryClinton,Alt-Right 0.0 : (0.0, 2.0) HillaryClinton,Anti-Govt 5.0 : (0.0, 5.0) HillaryClinton,Anti-Immigrant 142.0 : (2933.0, 3212.0) HillaryClinton,Anti-LGBT 4.0 : (10.0, 44.0) HillaryClinton,Anti-Muslim 4.0 : (2.0, 24.0) HillaryClinton,Black-Separatist 109.0 : (4113.0, 4388.0) HillaryClinton,Christian-Identity 5.0 : (0.0, 2.0) HillaryClinton,Ku-Klux-Klan 0.0 : (0.0, 0.0) HillaryClinton,Neo-Confederate 0.0 : (0.0, 0.0) HillaryClinton,Neo-Nazi 2.0 : (0.0, 4.0) HillaryClinton,Racist-Skinhead 0.0 : (0.0, 0.0) HillaryClinton,White-Nationalist 23.0 : (79.0, 144.0) SpeakerRyan,Alt-Right 1.0 : (0.0, 1.0) SpeakerRyan,Anti-Govt 7.0 : (0.0, 4.0) SpeakerRyan,Anti-Immigrant 442.0 : (664.0, 834.0) SpeakerRyan,Anti-LGBT 22.0 : (2.0, 23.0) SpeakerRyan,Anti-Muslim 27.0 : (0.0, 15.0) SpeakerRyan,Black-Separatist 6.0 : (860.0, 1034.0) SpeakerRyan,Christian-Identity 1.0 : (0.0, 1.0) SpeakerRyan,Ku-Klux-Klan 0.0 : (0.0, 0.0) SpeakerRyan,Neo-Confederate 0.0 : (0.0, 0.0) SpeakerRyan,Neo-Nazi 0.0 : (0.0, 4.0) SpeakerRyan,Racist-Skinhead 0.0 : (0.0, 0.0) SpeakerRyan,White-Nationalist 12.0 : (23.0, 65.0) realDonaldTrump,Alt-Right 54.0 : (0.0, 2.0) ; 52.96296296296296 : (0.0, 0.0) ; 6.648148148148148 : (0.0, 0.0) realDonaldTrump,Anti-Govt 239.0 : (0.0, 5.0) ; 92.93305439330544 : (0.0, 0.0) ; 6.510460251046025 : (0.0, 0.0) realDonaldTrump,Anti-Immigrant 4217.0 : (2936.0, 3213.0) ; 73.25847759070429 : (141.5390826873385, 147.87844036697248) ; 11.881669433246383 : (3.577196382428941, 3.6906005221932117) realDonaldTrump,Anti-LGBT 234.0 : (10.0, 44.0) ; 42.69230769230769 : (0.0, 420.030303030303) ; 9.786324786324787 : (0.0, 3.388888888888889) realDonaldTrump,Anti-Muslim 389.0 : (2.0, 24.0) ; 51.30848329048843 : (0.0, 0.0) ; 10.169665809768638 : (0.0, 0.0) realDonaldTrump,Black-Separatist 169.0 : (4120.0, 4393.0) realDonaldTrump,Christian-Identity 1.0 : (0.0, 2.0) realDonaldTrump,Ku-Klux-Klan 0.0 : (0.0, 0.0) realDonaldTrump,Neo-Confederate 0.0 : (0.0, 0.0) realDonaldTrump,Neo-Nazi 118.0 : (0.0, 4.0) ; 27.661016949152543 : (0.0, 0.0) ; 6.288135593220339 : (0.0, 0.0) realDonaldTrump,Racist-Skinhead 0.0 : (0.0, 0.0) realDonaldTrump,White-Nationalist 1010.0 : (79.0, 144.0) ; 48.526732673267325 : (200.2843137254902, 298.63440860215053) ; 9.973267326732673 : (3.0961538461538463, 3.407766990291262) tedcruz,Alt-Right 5.0 : (0.0, 1.0) tedcruz,Anti-Govt 10.0 : (0.0, 3.0) tedcruz,Anti-Immigrant 360.0 : (360.0, 505.0) tedcruz,Anti-LGBT 51.0 : (1.0, 17.0) ; 6.529411764705882 : (0.0, 0.0) ; 10.627450980392156 : (0.0, 0.0) tedcruz,Anti-Muslim 47.0 : (0.0, 13.0) ; 6.531914893617022 : (0.0, 0.0) ; 12.340425531914894 : (0.0, 0.0) tedcruz,Black-Separatist 2.0 : (481.0, 612.0) tedcruz,Christian-Identity 0.0 : (0.0, 1.0) tedcruz,Ku-Klux-Klan 0.0 : (0.0, 0.0) tedcruz,Neo-Confederate 0.0 : (0.0, 0.0) tedcruz,Neo-Nazi 2.0 : (0.0, 4.0) tedcruz,Racist-Skinhead 0.0 : (0.0, 0.0) tedcruz,White-Nationalist 17.0 : (15.0, 47.0) import scala.collection.immutable.ListMap myKeys: Iterable[String] = Set(BernieSanders,Alt-Right, BernieSanders,Anti-Govt, BernieSanders,Anti-Immigrant, BernieSanders,Anti-LGBT, BernieSanders,Anti-Muslim, BernieSanders,Black-Separatist, BernieSanders,Christian-Identity, BernieSanders,Ku-Klux-Klan, BernieSanders,Neo-Confederate, BernieSanders,Neo-Nazi, BernieSanders,Racist-Skinhead, BernieSanders,White-Nationalist, HillaryClinton,Alt-Right, HillaryClinton,Anti-Govt, HillaryClinton,Anti-Immigrant, HillaryClinton,Anti-LGBT, HillaryClinton,Anti-Muslim, HillaryClinton,Black-Separatist, HillaryClinton,Christian-Identity, HillaryClinton,Ku-Klux-Klan, HillaryClinton,Neo-Confederate, HillaryClinton,Neo-Nazi, HillaryClinton,Racist-Skinhead, HillaryClinton,White-Nationalist, SpeakerRyan,Alt-Right, SpeakerRyan,Anti-Govt, SpeakerRyan,Anti-Immigrant, SpeakerRyan,Anti-LGBT, SpeakerRyan,Anti-Muslim, SpeakerRyan,Black-Separatist, SpeakerRyan,Christian-Identity, SpeakerRyan,Ku-Klux-Klan, SpeakerRyan,Neo-Confederate, SpeakerRyan,Neo-Nazi, SpeakerRyan,Racist-Skinhead, SpeakerRyan,White-Nationalist, realDonaldTrump,Alt-Right, realDonaldTrump,Anti-Govt, realDonaldTrump,Anti-Immigrant, realDonaldTrump,Anti-LGBT, realDonaldTrump,Anti-Muslim, realDonaldTrump,Black-Separatist, realDonaldTrump,Christian-Identity, realDonaldTrump,Ku-Klux-Klan, realDonaldTrump,Neo-Confederate, realDonaldTrump,Neo-Nazi, realDonaldTrump,Racist-Skinhead, realDonaldTrump,White-Nationalist, tedcruz,Alt-Right, tedcruz,Anti-Govt, tedcruz,Anti-Immigrant, tedcruz,Anti-LGBT, tedcruz,Anti-Muslim, tedcruz,Black-Separatist, tedcruz,Christian-Identity, tedcruz,Ku-Klux-Klan, tedcruz,Neo-Confederate, tedcruz,Neo-Nazi, tedcruz,Racist-Skinhead, tedcruz,White-Nationalist)

Reference

Adams, A., & McCorkindale, T. (2013). Dialogue and transparency: A content analysis of how the 2012 presidential candidates used twitter. *Public Relations Review, 39*(4), 357-359.

Aldous, D. (2013). Interacting particle systems as stochastic social dynamics. *Bernoulli, 19*(4), 1122-1149.

Amy, B. (2011). *Poverty Rate Doubled in the Midwestern Rust Belt Over Past Decade.* Retrieved from http://abcnews.go.com/blogs/politics/2011/11/poverty-rate-doubled-in-the-midwestern-rust-belt-over-past-decade/

Apache Software Foundation. (n.d.). *Apache Spark™ is a fast and general engine for large-scale data processing. .* Retrieved from http://spark.apache.org/

Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. *Science, 348*(6239), 1130-1132.

Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological science, 26*(10), 1531-1542.

Berg, R. (2015). Trump's Latest: U.S. a "Dumping Ground" for Mexico.

Boshmaf, Y., Muslukhov, I., Beznosov, K., & Ripeanu, M. (2011). *The socialbot network: when bots socialize for fame and money.* Paper presented at the Proceedings of the 27th annual computer security applications conference.

Boyd, D., Golder, S., & Lotan, G. (2010). *Tweet, tweet, retweet: Conversational aspects of retweeting on twitter.* Paper presented at the System Sciences (HICSS), 2010 43rd Hawaii International Conference on.

Choy, M., Cheong, M. L., Laik, M. N., & Shung, K. P. (2011). A sentiment analysis of Singapore Presidential Election 2011 using Twitter data with census correction. *arXiv preprint arXiv:1108.5520*.

Christensen, M., & Christensen, C. (2008). The after-life of Eurovision 2003: Turkish and European social imaginaries and ephemeral communicative space. *Popular Communication, 6*(3), 155-172.

Cohen, C. (2017). *Donald Trump sexism tracker: Every offensive comment in one place.* Retrieved from http://www.telegraph.co.uk/women/politics/donald-trump-sexism-tracker-every-offensive-comment-in-one-place/

Conover, M., Ratkiewicz, J., Francisco, M. R., Gonçalves, B., Menczer, F., & Flammini, A. (2011). Political Polarization on Twitter. *ICWSM, 133*, 89-96.

Craig, M. A., & Richeson, J. A. (2014). On the precipice of a “majority-minority” America: Perceived status threat from the racial demographic shift affects White Americans’ political ideology. *Psychological Science, 25*(6), 1189-1197.

Curtis M. Wong. (2015). *GOP Presidential Hopeful Ben Carson Named To Southern Poverty Law Center’s Anti-Gay Extremist List.* Retrieved from http://www.huffingtonpost.com/2015/02/09/ben-carson-anti-gay-extremist-_n_6646994.html?utm_hp_ref=gay-voices

Dickerson, J. P., Kagan, V., & Subrahmanian, V. (2014). *Using sentiment to detect bots on Twitter: Are humans more opinionated than bots?* Paper presented at the Advances in Social Networks Analysis and Mining (ASONAM), 2014 IEEE/ACM International Conference on.

Fahey, M. (2017). *Donald Trump's Twitter engagement is stronger than ever.* Retrieved from http://www.cnbc.com/2017/02/16/donald-trumps-twitter-engagement-is-stronger-than-ever.html

Flitter, E., & Kahn, C. (2016). *Republicans, Democrats sharply divided over Muslims in America: Reuters/Ipsos poll.* Retrieved from http://www.reuters.com/article/us-usa-election-poll-muslims-idUSKCN0ZV20C

Frank, W. (2016). *Yes, Trump supporters voted to implement racism and bigotry.* Retrieved from http://www.dailykos.com/story/2016/12/4/1605960/-Yes-Trump-supporters-voted-to-implement-racism-and-bigotry

Freilich, J. D., & Alex Pridemore, W. (2006). Mismeasuring Militias: Limitations of Advocacy Group Data and of State-Level Studies of Paramilitary Groups. *Justice Quarterly, 23*(1), 147-162.

Gentzkow, M., & Shapiro, J. M. (2011). Ideological segregation online and offline. *The Quarterly Journal of Economics, 126*(4), 1799-1839.

Hall, A. B. (2015). What happens when extremists win primaries? *American Political Science Review, 109*(01), 18-42.

Hermida, A., Lewis, S. C., & Zamith, R. (2014). Sourcing the Arab Spring: A case study of Andy Carvin's sources on Twitter during the Tunisian and Egyptian revolutions. *Journal of Computer-Mediated Communication, 19*(3), 479-499.

Hogg, M. A. (2007). Uncertainty–identity theory. *Advances in experimental social psychology, 39*, 69-126.

Holley, P. (2016). *KKK's official newspaper supports Donald Trump for president.* Retrieved from https://www.washingtonpost.com/news/post-politics/wp/2016/11/01/the-kkks-official-newspaper-has-endorsed-donald-trump-for-president/?utm_term=.77d83582120b

Honey, C., & Herring, S. C. (2009). *Beyond microblogging: Conversation and collaboration via Twitter.* Paper presented at the System Sciences, 2009. HICSS'09. 42nd Hawaii International Conference on.

Internet Live Stats. (n.a.). *Twitter Usage Statistics.* Retrieved from http://www.internetlivestats.com/twitter-statistics/

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American society for information science and technology, 60*(11), 2169-2188.

Jonsson, P. (2011). *Annual report cites rise in hate groups, but some ask: What is hate?* Retrieved from http://www.csmonitor.com/USA/Society/2011/0223/Annual-report-cites-rise-in-hate-groups-but-some-ask-What-is-hate

Jost, J. T., Glaser, J., Kruglanski, A. W., & Sulloway, F. J. (2003). Political conservatism as motivated social cognition: American Psychological Association.

Kouloumpis, E., Wilson, T., & Moore, J. D. (2011). Twitter sentiment analysis: The good the bad and the omg! *Icwsm, 11*(538-541), 164.

Kruglanski, A. W. (1996). Motivated social cognition: Principles of the interface.

Kruglanski, A. W., Pierro, A., Mannetti, L., & De Grada, E. (2006). Groups as epistemic providers: need for closure and the unfolding of group-centrism. *Psychological review, 113*(1), 84.

Le Miere, J. (2016). *President Obama Speech Live Stream: Donald Trump's Election Win To Be Addressed In Statement.* Retrieved from http://www.ibtimes.com/president-obama-speech-live-stream-donald-trumps-election-win-be-addressed-statement-2444127

Major, B., Blodorn, A., & Major Blascovich, G. (2016). The threat of increasing diversity: Why many White Americans support Trump in the 2016 presidential election. *Group Processes & Intergroup Relations*, 1368430216677304.

Margolis, J. (2016). Hillary Clinton's stand on NAFTA and the TPP: It's complicated, and evolving.

Marlow, C. A. (2005). *The structural determinants of media contagion.* Citeseer.

Metaxas, P. T., Mustafaraj, E., Wong, K., Zeng, L., O'Keefe, M., & Finn, S. (2015). *What Do Retweets Indicate? Results from User Survey and Meta-Review of Research.* Paper presented at the ICWSM.

Muro, M. (2016). *Manufacturing Jobs Aren't Coming Back.* Retrieved from https://www.technologyreview.com/s/602869/manufacturing-jobs-arent-coming-back/

Nawaz, M. (2016). *I'm A Muslim Reformer. Why Am I Being Smeared as an 'Anti-Muslim Extremist'?* Retrieved from http://www.thedailybeast.com/articles/2016/10/29/i-m-a-muslim-reformer-why-am-i-being-smeared-as-an-anti-muslim-extremist

Neiwert, D., & Posner, S. (2016). Meet the Horde of Neo-Nazis, Klansmen, and Other Extremist Leaders Endorsing Donald Trump.

Pfau, M., Houston, J. B., & Semmler, S. M. (2007). *Mediating the vote: The changing media landscape in US presidential campaigns*: Rowman & Littlefield.

Revesz, R. (2016). *Donald Trump still wants to ban Muslims from US and build 'registry' despite backtracking after election.* Retrieved from http://www.independent.co.uk/news/world/americas/donald-trump-muslim-ban-registry-berlin-attack-twitter-you-know-my-plans-immigration-racism-a7489611.html

Runciman, W. G. (1966). Relative deprivation & social justice: Study attitudes social inequality in 20th century England.

Saif, H., He, Y., & Alani, H. (2012). Semantic sentiment analysis of twitter. *The Semantic Web–ISWC 2012*, 508-524.

Scott, R. (2015). *Fast Track to Lost Jobs and Lower Wages.* Retrieved from http://www.epi.org/blog/fast-track-to-lost-jobs-and-lower-wages/

Smith, A. (2009). The Internet's role in campaign 2008. *Pew Internet & American Life Project, 15*.

Southern Poverty Law Center. (n.d.-a). *Extermist Files.* Retrieved from https://www.splcenter.org/fighting-hate/extremist-files

Southern Poverty Law Center. (n.d.-b). *What We Do.* Retrieved from https://www.splcenter.org/what-we-do

Stephan, C., & Stephan, W. (2000). An integrated treat theory of prejudice. Reduciing prejudice and discrimination: Mahwah. Psychology press.

The Texas Politics Project. (2016). *Banning Muslims from Entering U.S.* Retrieved from https://texaspolitics.utexas.edu/set/banning-muslims-entering-us-june-2016#party-id

Time. (2015). *Here's Donald Trump's Presidential Announcement Speech.* Retrieved from http://time.com/3923128/donald-trump-announcement-speech/

Times, T. W. (2017). *Should President Trump quit Twitter? Hell no!* Retrieved from http://www.washingtontimes.com/news/2017/mar/23/donald-trump-must-keep-using-twitter/

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2010). Predicting elections with twitter: What 140 characters reveal about political sentiment. *ICWSM, 10*(1), 178-185.

Twitter Inc. (2017). *Twitter Developer Documentation.* Retrieved from https://dev.twitter.com/rest/public

Van Hiel, A., Pandelaere, M., & Duriez, B. (2004). The impact of need for closure on conservative beliefs and racism: Differential mediation by authoritarian submission and authoritarian dominance. *Personality and Social Psychology Bulletin, 30*(7), 824-837.

Wald, R., Khoshgoftaar, T. M., Napolitano, A., & Sumner, C. (2013). *Predicting susceptibility to social bots on twitter.* Paper presented at the Information Reuse and Integration (IRI), 2013 IEEE 14th International Conference on.

Walker, I., & Pettigrew, T. F. (1984). Relative deprivation theory: An overview and conceptual critique. *British Journal of Social Psychology, 23*(4), 301-310.